

Exurban land cover and land market evolution: Analysis, review
and computational experimentation of spatial and agent
heterogeneity from the bottom up

by

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Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Preface Statement

I choose the manuscript option to compile my Ph.D. dissertation under the guidelines provided by the joint Waterloo-Laurier Graduate Program in Geography. Three manuscripts are presented in Chapter 3 to 5 respectively. I am the first author for the three manuscripts which are dominated by my intellectual effort and written by me. The status of the submissions and the roles of author and co-authors are explained in detailed below respectively. In order to keep a consistent format of spelling, references and other matters, and to address comments listed by defense committee members, minor changes are adopted to original manuscripts to comprise Chapter 3 to 5.

The first manuscript is titled “Land-cover convergence among exurban residential parcels: a case study in Southeastern Michigan.” In this manuscript, I conceived of the study under the supervision of the two co-authors, Dr. Derek Robinson and Dr. Dawn Parker. I carried out the data analysis, manuscript writing and revision. Dr. Robinson provided the original dataset. He and Dr. Parker actively participated in the discussions of critical analysis of the results and reviewing the manuscript. The preliminary results were presented by my supervisor, Dr. Dawn Parker at the Ecosummit landscape ecology conference in Columbus, Ohio in October 2012. Based on this presentation, the paper was invited for submission to a special issue of Landscape Ecology.

The second manuscript entitled “A review of urban residential choice models using agent-based modeling” was submitted to Environment and Planning B in October 2012 and is currently under review. In this manuscript, I designed the review criteria, conducted the literature review, summarized and compared models, systemized the information and design concepts from more than 50 ABMs, identified their critical differences and similarities, and wrote and revised the manuscript under the supervision of Dr. Dawn Parker. Dr. Parker and the other two co-authors, Dr. Tatiana Filatova and Dr.

Shipeng Sun, provided critical comments on the draft, suggested additional references, and participated in editing and reviewing the draft. All authors read and approved the final manuscript.

The third manuscript entitled “Effects of agent heterogeneity in the presence of a land-market: a systematic test in an agent-based laboratory” was submitted to Computers, Environment and Urban Systems in June 2012 and received very positive reviews from the two reviewers and the editor. I lead the revision effort and currently this manuscript is the second round of review after the revision according to reviewers’ comments. In this manuscript, I designed the experiments, wrote the R code for the statistical analysis and visualization of the simulation results, analyzed the results using statistical models and landscape pattern metrics, wrote, and revised the manuscript under the supervision of Dr. Dawn Parker. Dr. Shipeng Sun and Dr. Dawn Parker developed this model, based in part on previous models by Dr. Filatova and Dr. Robinson. I also participated in testing and debugging of the model. (The details of the development of the model can be found in a manuscript entitled “Significance and complexity of market impacts on land-use change: An agent-based experiment”. It was submitted to the Annals of American Association of Geography and received very positive first-round reviews. I am also a co-author on that manuscript.). The other three co-authors, Dr. Parker, Dr. Sun and Dr. Filatova participated in editing and providing critical comments on the manuscript. All authors read and approved the final manuscript.

Signatures of co-authors indicating that they are in agreement with the evaluation of the roles and contributions of the various authors are provided as below:

First manuscript: Land-cover convergence among exurban residential parcels: a case study in Southeastern Michigan

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Third manuscript: Effects of agent heterogeneity in the presence of a land-market: a systematic test in an agent-based laboratory

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Abstract

This dissertation investigates selected empirical and theoretical aspects of land-use and land-cover change (LUCC) in exurban areas. Two challenges – observation and monitoring of LUCC, and spatially explicit modeling, are addressed using three main approaches – measuring, reviewing and agent-based modeling (ABM). All of these approaches focus on LUCC at the individual household level, investigating how micro-scale elements interact to influence macro-scale functional patterns—bottom-up analysis.

First, the temporal change of the quantity and pattern of land-cover types within exurban residential parcels in three townships in the southeastern Michigan is examined using landscape metrics and local indicators of spatial association at the parcel and parcel-neighborhood level respectively. The results demonstrate that the number and area of exurban residential parcels increased steadily from 1960 to 2000, and different land-cover types have distinctive temporal changes over time. The results also indicate that there is a convergence process at the neighborhood level through which the quantity and pattern of land cover in parcels conform with the neighborhood appearance.

Second, 51 urban residential choice models based on ABM are reviewed. The results divide these models into three categories (i.e. models based on classical theories, models focusing on different stages of urbanization process; and integrated ABM and microsimulation models). This review also compares the differences among these models in their representations of three essential features brought by the technique of ABM: agent heterogeneity, the land market and output measurement. Challenges in incorporating these features, such as the trade-off between the simplicity and abstraction of model and the complexity of urban residential system, interactions of multiple features and demands for data at individual level, are also discussed.

Third, the effects of agent heterogeneity on spatial and socioeconomic outcomes under

different levels of land-market representations are explored through three experiments using a stylized agent-based land-market model. The results reveal that budget heterogeneity has prominent effects on socioeconomic outcomes, while preference heterogeneity is highly pertinent to spatial outcomes. The relationship between agent heterogeneity and macro-measures becomes more complex as more land-market mechanisms are represented. The results also imply that land-market representation (e.g., competitive bidding) is indispensable to reproduce the results of classical urban land market models (e.g., monocentric city model) in a spatial ABM when agents are heterogeneous.

Key words: exurban development, land-cover change, agent-based modeling, land market, agent heterogeneity

Acknowledgements

Today is the mid-autumn day in China. It is the day when the moon is experiencing the eighth full phase in the Chinese lunar calendar. It is a traditional Chinese festival in which relatives and close friends reunite. The reunion is, on the one hand, to celebrate the harvest in the autumn as the Oktoberfest in Kitchener-Waterloo, and on the other hand, to provide an opportunity to gather relatives and close friends together as the Thanksgiving in western Countries. The traditional snack prepared for this particular day is the mooncake. A typical mooncake is a round pastry which resembles the moon and has the implication of reunion, perfection, and happiness. This festival has been listed as an “intangible culture heritage” in China and made as a public holiday. In the past 28 years, I have spent more than four years in three cities and celebrated this festival. These past experiences, I think, are the nodes which can artfully connect my academic life and my mundane life.

I was born in Chengdu, which is famous for its temperament of leisure and comfort. I spent 18 years in Chengdu before college and have strong sense of affiliation and nostalgia for this city. Now most of my classmates from middle schools have started to work across China. So that means, at the same time I am writing the acknowledgement, some of them are on the way back to the hometown. During the last 10 years I spent outside Chengdu, they told me the development in Chengdu from time to time. The leisure city in my memory has changed tremendously in the last decade. Road tunnels, large shopping malls, and high-tech zones sprouted out and the city expanded ceaselessly. While the real spirit of the city, life enjoyment with playing Mahjong under the shade of trees, eating delicate Szechuan cuisine in the midnights, and drinking jasmine tea in public parks faded away over time.

I spent 6 years in Beijing for the undergraduate and master degree’s study. Beijing is, by all means, a complex city. In my opinion, it tries very hard to work as the center of commerce, culture, and politics simultaneously. It also bears too much burden of history and development at the same time. In Beijing, we can find a distinctive residential

system, *Hutong*, in which ordinary people live in a crowded and humble accommodation but with higher level of interactions among neighbors. Staying under the same roof is rather an emotional expression and means more mutual support rather than tolerating the disadvantages. In the meantime, skyscrapers and post-modern buildings grew constantly, like the Olympic stadium (the Bird Nest and the Water Cube), and the central television building. Visiting the CBD in Beijing in rush hour would be a disaster for a “foreigner” in this city, regardless of any transport methods you choose. You will experience either “people mountain people sea” if you choose the subway, or terrible traffic jam if you choose taxi, or detrimental air and noise even if you choose walk or bicycle. It seems there are always dilemmas about the land-use issues in Beijing. During major festivals and public holidays, Beijing is facing the extensive challenges of accommodation, transportation and safety to cater all the tourists and nostalgic migrants.

In the last four years, I was living and studying in Waterloo, a pretty “small” city in Canada (However, Waterloo region was ranked as number two on the performance of economy among Canadian urban centers). Even if it is a relative small city, diversity sprawls out the whole city. It has a large amount of international students here since it has two well-known universities. It works as a new hub for the high-tech development in Canada surrounding the flagship blackberry company, RIM. It also has a heritage of German immigrants. The district along the University Avenue between University of Waterloo and Wilfrid Laurier University was described as a “student ghetto” with occasional vandalism and accidents two years ago. And recently several high rise condominiums in the same district are in the final stage of construction and ready to welcome the increasing amount of students here. Homeowners who used to work in RIM are moving out the city due to the layoffs and a restrictive requirement of a rental housing license. During the festival, my Chinese fellow students are gathering together, eating mooncakes bought from local Chinese grocery stores in Waterloo or Toronto, telecommunicating with friends and relatives in the other half of planet Earth, and enjoying festival shows online.

It seems the land use continuously changes in all the three cities, whether it is large or small. Also it looks like people can embrace the traditional customs and modern technologies at the same time. When new conflicts emerge and hamper our development,

we – human beings – are adept at adjusting and improving. This is also true in academic development. A Ph.D study is a path toward improving the academic knowledge in a specific narrow way with innovative methods and results. It is not a leisure path, and therefore I want to express my sincere appreciation to all the people helping me during this path.

First and foremost, I want to express my gratitude to my Ph.D. supervisor, Dr. Dawn Parker. In the past three years, her enthusiasm, knowledge and encouragement always inspire me to hurdle the obstacles in completing all the research. She gave a first impression of strictness in my comprehensive exam. But after she became my supervisor and I took her elaborately prepared course, I start to find that she really care about students. And insightful discussion with her becomes weekly intellectual challenge and enjoyment, which guide the path for me to be an independent researcher with integrity.

I would also like to thank my former supervisor, Dr. Jonathan Li, for helping me getting through the first year in Canada. In addition, I am indebted to many colleagues for their generous help. I am especially grateful to Shipeng Sun, Tatiana Filatova, and Derek Robinson. Because of your kind assistances in reviewing and commenting on my work, I am able to finish the Ph.D study with fruitful outputs. All of you are great persons who are not reluctant to share your experiences in not only academic sphere but also social activities. I really enjoy spending time with all of you, and love your sense of humor. I am hoping we can continue our collaboration in the future.

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Friends play a really important role in accompanying me accomplishing the fifty-month living in Canada regardless of where you are living. It would be a really tough journey to

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Chapter 1 Introduction

1.1 Scope of the thesis

Rapid and extensive land-cover and land-use change (LUCC) have spread in exurban areas in the United States for the past several decades. A series of approaches have been developed to address the challenges brought by the LUCC process, and new datasets and modeling techniques have emerged. Recent studies in exurban LUCC have heightened the need for understanding the process from the perspective of decision makers (e.g., household, developer) because they are the direct driving forces for the change. Although there are increasing attempts to measure and simulate the temporal changes of landscape patterns in exurban areas from the bottom up, a considerable number of research problems are still in the need of being explored. Thus, this thesis aims to address a subset of these outstanding research problems related to exurban LUCC through three major approaches: measuring, reviewing, and modeling.

1.2 Context and motivation

1.2.1 LUCC and exurban development

LUCC is a fundamental component in global environmental studies, and a key element of two major global change research programs: the International Geosphere-Biosphere Programme (IGBP) and the International Human Dimensions Programme on Global Environmental Change (IHDP) (Rindfuss et al., 2004; Turner2007). Lambin et al. (2001, page 262) defined land cover as “the biophysical attribute of the earth’s surface”, and land use as “the human purpose or management applied to these attributes”. Changes in land use and land cover are so pervasive that they impact some main aspects of the Earth system functioning (e.g., biotic diversity, climate change,

soil degradation) and the life of human beings. Researchers have concluded that LUCC is the result of integrated interactions between humans and the Earth system (Foley et al., 2005; Lambin et al., 2001).

Urban areas are hotspots that drive LUCC and environmental change at multiple scales. During the last several decades, human have been experiencing a dramatic shift to urban living. Urban population now accounts for 52.08% of total population (3.63 billion/6.97 billion), and developing regions will account for 96.58% (2.26 billion/ 2.34 billion) of the net growth in global population in 2050 (UN, 2012). This unprecedented rate of urban population growth is accompanied by rapidly growth in city size and demographic changes. The process of urbanization raise growing concerns regarding its environmental consequences and implications for global change and sustainability (Grimm et al., 2008; Kalnay and Cai, 2003; Rosenzweig et al., 2010; Seto et al., 2012).

Different regions are undergoing different stages and levels of urbanization. Recently, a progressive phenomenon spreading outward in suburban and exurban areas, namely, urban sprawl, has gained its momentum in both North American and European countries and in some developing countries (such as India and China) (Jat et al., 2008; Lopez and Hynes, 2003; Mann; Skaburskis, 2006; Song and Knaap, 2004b; Xie et al., 2007). Although there is no standard quantitative definition¹ of exurban developments and multiple definitions can be found in previous studies (Ban and Ahlqvist, 2007; Clark et al., 2009; Theobald, 2004), researchers are in consensus that exurban sprawl is a relative inefficient urbanization process due to its direct and indirect influences on urban life (Brueckner, 2000; Ewing, 2008a; Nechyba and Walsh, 2004; Torrens, 2008), including psychic cost (deprivation of environment and access), excessive travel and congestion, cost of energy, environment, infrastructure and services, loss of agricultural land and open space, and downtown decay.

¹ In this dissertation, consistent with a previous study (Brown et al., 2005a), I used the definition of exurban area determined by housing density at the block-group level derived from U.S. census. The housing density in exurban area is defined as being between 1 unit per 1 acre and 40 acres.

Linking the process of exurban sprawl with the patterns of exurban LUCC plays an important role in understanding and modeling human-environment interactions in the exurban context (Clark et al., 2009; Nagendra et al., 2004). Quantifying spatial heterogeneity of LUCC over time provides the first step to understand the effects of LUCC on ecological processes. Approaches to measure LUCC are facilitated by development of remote sensing (RS) techniques and geographic information system (GIS) (Goodchild, 2004) and the developments in the techniques of image classification and spatial analysis (Herold et al., 2005; Ji et al., 2006).

Landscape ecology has recently been widely used to study the interactions between landscape patterns and ecological consequences (Alberti, 2008; Nagendra et al., 2004; Turner et al., 2001; Wu, 2010). It has been found that landscape pattern indices may reflect processes operating on different scales, but also that the spatial patterns could have effects on ecological processes (Turner, 1989). Various spatial analysis methods and landscape metrics have been developed to document the temporal changes of LUCC patterns at different scales. For example, the increasing land fragmentation resulting from urban sprawl in the state of Maryland from 1973 to 2000 was examined through six selected landscape metrics (i.e., patch density, mean patch size, mean perimeter-to-area ratio, contrasting edge ratio, contrasting edge proportion, and mean dispersion) by Irwin and Bockstael (2007). Meanwhile, researchers have attempted to relate these measures of spatial pattern to the properties and processes of ecosystem functioning (Wu, 2008), e.g., provision of goods and services, regulation and moderation of climate, storage and processing of chemicals and provision of cultural and recreational enjoyment. In a review, Alberti (2005) found that the fragmentation of urban development can result in various effects on ecosystem functions, including segregation and deterioration of natural habitats, loss of biodiversity and increased vulnerability of species composition, disruptive damage to hydrological system, and disturbance of energy flow and nutrient cycling.

With a deeper understanding of the linkage between the process of urban sprawl and the pattern of exurban LUCC, researchers have come to view the exurban

system as a complex system where the spatial and social structures of a city are emerging from multiple interactive decisions of intelligent entities from the bottom up (Batty, 2005; Benenson and Torrens, 2004a; Bretagnolle and Pumain, 2006; Liu et al., 2007). The complex system has the characteristics of emergence, nonlinearity, adaptive, and path dependence (Arthur, 1988; Batty, 2005; Brown et al., 2005b; Holland, 1998). In the past several decades, a wide range of models have been developed to capture LUCC in the context of the exurban system, because models can link the LUCC process with patterns and investigate a broad spectrum of drivers and consequences of LUCC (Costanza and Ruth, 1998; Verburg et al., 2004). In addition, spatially explicit and dynamic LUCC models can represent the location and timing of change simultaneously.

1.2.2 Simulating approaches for exurban LUCC

Approaches to modeling exurban LUCC change range from simple mathematical models to intricate rule-based ones, from top-down methods at an aggregated scale to bottom-up methods at the cellular or agent level. These approaches include equation-based models (e.g., models based on gravity theory), system dynamics models, statistical models, Markov and cellular automata (CA) models, models based on other techniques (e.g., fractal theory, fuzzy logic, neural network, and Bayesian probabilities theory), and hybrid models that integrate multiple modeling techniques. The history of model improvement and the advantages and drawbacks of each approach are reviewed extensively with different emphases (Agarwal, 2002; Batty, 1994; Berling-Wolff and Wu, 2004; Brown et al., 2004b; Irwin and Geoghegan, 2001; Lambin et al., 2001; Parker et al., 2003; Verburg et al., 2004).

Beyond the methods mentioned above, a relatively new approach, agent-based modeling (ABM), is increasingly used to simulate exurban LUCC. ABM is a modeling tool which can simulate heterogeneous decision makers and their actions (Parker et al., 2012b). ABM is regarded as a natural solution adopted by modelers to disentangle the complexity (e.g., emergence, path dependence, and agent

heterogeneity) in exurban systems for several reasons (Benenson and Torrens, 2004a; Brown et al., 2008; Crawford et al., 2005; Manson et al., 2012; O'Sullivan et al., 2012; Parker et al., 2003). First, it can simulate the individual behaviors of multiple heterogeneous agents, and the interactions among agents and between agents and the environment. Second, it can relax some restrictions of previous models. For example, agents can be adaptive and cognitive; agents are no longer utility maximizers; agents can move across space; and they can participate in the negotiations with other agents. Third, the flexibility in agents' representation enables models to explore a broader dimension of issues in exurban LUCC, ranging from policy evaluations to development assessments. In summary, ABMs work as a vehicle to link emerging patterns with processes that operate on multiple scales in a bottom-up means.

Among all the efforts and projects that aim to investigate the linkage between the process of exurban residential development and LUCC patterns, this thesis is part of a large research project called SLUCE (Spatial Land Use Change and Ecological Effects at the rural-urban interface). The SLUCE project intends to conduct an integrated investigation of the structure and effects of land markets, land management, temporal change of land cover and land use, and land-atmosphere carbon budgets in exurban residential areas in Southeastern Michigan, USA. This thesis is a component of the larger project that focuses on empirical measurement temporal change of land-cover within exurban residential parcels and theoretical exploration of the effects of agent heterogeneity and land market representations (i.e., the representation of land market processes, such as resource constraints and competitive bidding, and actors' behaviors within these processes) on model outcomes.

1.3 Goal, Objectives and Research Questions

1.3.1 Goal and objectives

Four major challenges in land change science for global environment change and

sustainability are summarized and addressed by Turner et al. al. (2007). They are: (1) observation and monitoring of LUCC at different scales; (2) understanding the coupled system (e.g., causes and feedbacks); (3) using the understanding for spatially explicit modeling; and (4) assessment of consequent impacts (e.g., vulnerability, resilience, or sustainability). The main goal of this thesis is to acquire insights into spatial and agent heterogeneity of LUCC in an exurban context with land market representation, with a focus on the first (i.e. spatial analysis of observation and monitoring data) and third (i.e. modeling) challenges. Specifically, this thesis intends to connect LUCC patterns with the processes of residential choice at micro-level. It will, on the one hand, empirically enrich our understanding of LUCC at individual parcel level and confirm some inferences made by previous studies, and on the other hand, be of use to theoretically improve our modeling practice and to reconcile some conflicts in previous findings. In other words, this study provides a close link to previous research and attempts to analyze and simulate LUCC from the household perspective. To achieve this purpose, the following objectives were defined:

- Analyze temporal changes of the quantity and patterns of land covers within exurban residential parcel in a case study in Southeastern Michigan (SEM) over the past four decades (1960 to 2000)
- Explore and test the features of land-cover patterns in exurban SEM suggested by previous research (An et al., 2010; Nassauer et al., 2009; Robinson, 2012); specifically, examine the temporal changes of land covers grouped by parcel size, and test for a convergent trend in the quantity and pattern of land covers due to neighborhood effects.
- Summarize and compare the applications of agent-based modeling in simulating residential choices in an urban context, with a focus on the progress of their representation of agent heterogeneity, land market processes, and output measurement.
- Identify and discuss the research gaps underlying these simulation attempts in order to theoretically and empirically improve developments of ABMs.
- Use a stylized Agent-based land market model (ABLMM), named LUXE

(Land Use in eXurban Environments) which simulates residential choices in a land market, to investigate the multidimensional effects of agent heterogeneity on spatial and socioeconomic patterns of development under different degrees of market representation.

1.3.2 Research questions

To reach the goal, the following six research questions were formulated:

Q1: How are land-cover composition and configuration altered at the parcel level during the period from 1960 to 2000 in the exurban areas of Southeastern Michigan?

Q2: Is the land-cover pattern of individual parcels consistent with the neighborhood appearance over time? Is it possible to identify representative parcels that have experienced a convergence process, in which land-cover quantities and/or patterns in exurban residential parcels conform the neighborhood appearance?

Q3: How do existing applications of ABMs fill in the continuum that runs from purely theoretical to extensively empirical models?

Q4: What are the differences among existing ABMs that simulating urban residential choices in handling agent heterogeneity, land market components and output measurement?

Q5: How does agents' heterogeneity in incomes and in locational preferences theoretically affect emerging land-use patterns? How does the degree of heterogeneity in the agents' population affect spatial and economic phenomena? And do the collective effects from multiple sources of agent heterogeneity vary under different market representations?

Q6: Do the outcomes of the theoretical monocentric city differ in different representations of market elements, especially in the existence of agent heterogeneity? Are different representations of market elements able to reconcile some conflicting results about the effects of agent heterogeneity drawn by other models?

1.4 Thesis Outline

The current thesis consists of six chapters. After the *Introduction*, *Chapter 2* briefly introduces and explains the methodology used in the thesis. It consists of land-cover change measurement using landscape metrics and local indicators of spatial association, a extensive review of ABMs simulating residential choices in urban areas, and an experimental design to explore the effects of land market representations and agent heterogeneity on the outputs.

Chapter 3 examines the temporal change of land cover composition and configuration at the parcel level in exurban areas of southeastern Michigan. The differences in quantities and patterns of land covers among nine levels parcel size are presented, and the similarity of landscape design in the neighborhood is tested.

Chapter 4 offers a review of the developments in ABMs of urban residential choices. Fifty-one relevant models were reviewed, which fall into three general categories – (i) urban land-use models based on classical theories; (ii) different stages of the urbanization process; and (iii) models integrated with ABM and microsimulation. Their features are summarized and compared within each category. In addition, this chapter focuses on the applications of three fundamental features: agent heterogeneity, representation of land market processes, and measurement of a broad range of outputs.

Based on a stylized agent-based land market model, LUXE (Land Use in eXurban Environments), *Chapter 5* presents the effects of multidimensional agents' heterogeneity on the spatial and socioeconomic patterns of urban land use change under various market representations. Two sources of agent heterogeneity are examined: budget heterogeneity, which imposes constraints on the affordability of land, and preference heterogeneity, which determines location choice. The effects of the two dimensions of agents' heterogeneity are systematically explored across different market representations (e.g., heterogeneous preferences, budget constraints, and competitive bidding) through three experiments.

The last *Conclusion Chapter* summarizes the findings from the previous three chapters. It provides general answers to the six research questions in section 1.2.2. It also provides a discussion on the further directions to improve current work.

Chapter 2 Methodology

The core challenge in this thesis is to understand exurban residential development from the bottom up. In order to disentangle the complexity of LUCC in exurban areas, two streams of methods are adopted to solve the observation and monitoring (i.e., spatial analysis of land-cover and parcel data) challenge and the modeling challenge addressed by Turner et al. (2007). This chapter offers a general framework of the two streams of methods used in this thesis (Figure 2-1).

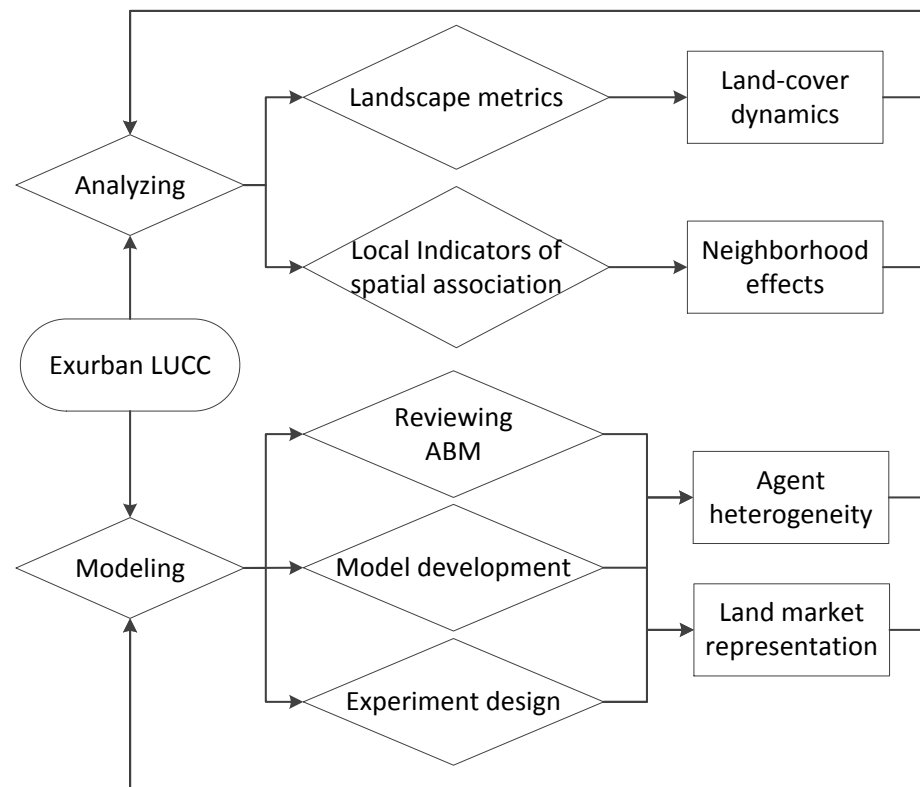


Figure 2-1 General framework of the thesis (The ellipse represents the core object. The diamonds represent different methods. The rectangles represent study objects.)

2.1 Analyzing temporal changes of exurban LUCC

The first series of methods are used to measure the temporal changes of exurban

LUCC from the parcel perspective. These analyses are based on a dataset constructed by Robinson (2012). To address the first two research questions proposed by the thesis, two kinds of statistics are calculated for four major land covers (i.e. tree cover, impervious structure, maintained lawn and open fields) within exurban residential parcels and in the neighborhood respectively. The other three land-cover types (i.e. saturated areas, open water, cropland) were excluded because they are not common features found in exurban residential parcels.

The first kind of statistics are landscape metrics, which are used for analyzing the spatiotemporal changes of land-cover quantity and patterns (McGarigal et al., 2002). Five metrics are chosen because they can capture the main characteristics of landscape patterns, and they are consistent with the previous study by Robinson (2012). The five metrics describe different properties of landscape pattern. For each land-cover type, they are: (1) total land cover for the quantity; (2) number of patches and (3) mean patch size for the degree of fragmentation, (4) edge density for the edge characteristics; and (5) area weighted mean shape index.

The second kind of statistics includes two local indicators of spatial associations calculated by Geoda (Anselin et al., 2006). To investigate the neighborhood effects on the quantity and patterns of land covers in nearby residential parcels, the local Moran's I is used to measure spatial similarity of each landscape in a Queen's case of neighborhood design (i.e., nearest 8 neighbors). The temporal change of average local Moran's I will indicate whether the similarity of landscape patterns in the neighborhood becomes greater over time. In addition, to identify parcels that are significantly similar to their neighbors, the cluster index is calculated for all the parcels. For each period, parcels are further divided into two subsets: one consisting of newly developed parcels in that period and the other composed of parcels developed before that period. The temporal changes in the numbers of parcels that are significantly similar to their neighbors from the two subsets of parcels can indicate which subset is the major force for the spatial similarity of landscape patterns in the neighborhood.

2.2 Exploring exurban LUCC by ABM

After the measurement efforts, the technique of agent-based modeling is adopted to link the theoretical patterns of exurban development and individual households from the bottom up. To achieve the goal of experiment design, I first reviewed 51 ABMs in the domain of urban land-use change models. Two important features (among others), the representation of land-market process and agent heterogeneity, are identified as playing an important role in affecting patterns and characteristics of exurban development. In addition to the review, a stylized agent-based land market model, LUXE (Land Use in eXurban Environments) was developed by the SLUCE2 research team (Parker et al., 2012a; Sun et al., in review). Then a series of experiments were designed to examine effects of multi-dimensional agent heterogeneity under different market conditions.

The LUXE model is developed on the basis of two previous ABMs, ALMA and SOME (see Sun et al., in review for more details). It can simulate exchange and transaction prices of land between sellers (i.e. landowners) and buyers (i.e. households). Four levels of market representation, from the most minimal scenario without either budget constraints or competitive bidding to a complex scenario with both budget constraints and competitive bidding, were designed by the team to explore the impacts of land market representations on model outcomes. I measured the outputs by six metrics (i.e. mean transport cost, total developed parcels, edge density, mean utility, mean transaction price and Theil index) from landscape, socio-economic and individual perspectives.

I designed three series of experiments to gradually disentangle the collective effects of multi-dimensional agent heterogeneity and multi-level land market representations. In the first experiment, agent heterogeneity is introduced by changing

either buyers' preferences or their budgets². The Wilcoxon Signed-Rank Test is used to test whether the six metrics between heterogeneous agents and homogeneous agents differ under each market level. In the second experiment, the magnitudes of heterogeneity in budget and preference are increased gradually and respectively in each market level. The results can provide insights on the effects of variations of agent heterogeneity on spatial and socioeconomic outputs. The standard deviations of both preference and budget are changed simultaneously in the last experiment to evaluate the collective effects of multiple sources of agent heterogeneity under each market level.

In summary, a framework of various methods are implemented to measure and model exurban development from the bottom up, including measurement of landscape patterns and spatial autocorrelation, reviewing and developing of agent-based land-use change models, and designing of experiments. This framework is helpful to understand exurban LUCC at an individual household level because it can combine empirical findings from measuring land-cover dynamics and theoretical findings from modeling land-use changes. It also combines inductive and deductive methods together to simulate emergent patterns of exurban LUCC from cumulative effect of individual behaviors.

² Budget and preference follow a normal distribution. When agents are heterogeneous, the mean values of budget and preference remains constant but their standard deviation values vary. When agents are homogeneous, the standard deviations of budget and preference are 0.

Chapter 3 Land-cover convergence among exurban residential parcels: a case study in Southeastern Michigan

3.1 Introduction

Rapid urbanization process have changed regional landscapes at an unprecedented speed over the past several decades (Elvidge et al., 2004). Between 1950 and 2011, the urban population has increased nearly fivefold from 0.75 to approximately 3.6 billion worldwide (UN, 2012). A similar situation has been observed in developed countries. Alig et al. (2004) found, in the United States, that land devoted to developed area as a percentage of total land area increased from 3.9 to 5.2% between 1982 and 1997, and they anticipate that this trend will continue over the next 25 years. Urbanization in the United States is manifested by an increasing density in existing urban areas coupled with a low-density expansion along the urban-rural fringe (i.e. exurban areas).

Although definitions and divisions of land from urban to suburban, exurban, and rural vary from study to study, there is consensus that, compared to the amount of area classified as urban, the amount of area classified as exurban is substantially greater (Ban and Ahlqvist, 2007; Berube et al., 2006; Brown et al., 2005a; Clark et al., 2009; Theobald, 2001, 2005). In addition, housing and population density is much lower in exurban areas than urban areas. Brown et al. (2005a) found that, in the conterminous United States, the area of land classified as exurban (housing density between 1 unit per 1 acre to 40 acres) increased from about 5% (270 608 km²) of total land area of the conterminous U.S. in 1950 to about 25% (1.39 million km²) by 2000. In contrast, over the same period, the area of land classified as urban (housing density greater than 1 unit per 1 acre) only increased from less than 1% (19 296 km²) to nearly 2% (93 538 km²). Based on demographic and economic data from 1990 to

2005, the typical occupation of land per home in exurban census tracts is 14 acres (Berube et al., 2006), which is higher than the national average (0.8 acres per home). Based on another classification of exurban area at the county level, Nelson (1992) estimated that, in 1985, average population density in exurbia is about 24 persons per km², in contrast to about 372 and 199 in urban and suburban areas respectively.

The fast-paced growth of low-density exurban development draws attention to its potential impacts on ecosystems and social life – landscape fragmentation (Irwin and Bockstael, 2007) and consequent degradation of habitat and natural resources; excessive travel and accompanying congestion and increased greenhouse gas emissions; increasing costs in energy, infrastructure and public service; loss of agricultural land or open space; residential segregation and downtown decay. (Ewing, 2008b; Nechyba and Walsh, 2004).

Measuring and monitoring land-use and land-cover change (LUCC) plays a fundamental role in understanding exurban residential development and its consequences. Existing literature describes the quantity and pattern of LUCC at national or regional scales (Clark et al., 2009; Irwin and Bockstael, 2007; Theobald, 2005). However, little is known about the temporal change of land-cover patterns within residential parcels (Robinson, 2012). Current results show that the quantity and pattern of land-cover types within parcels exhibit some distinctive features. For example, not only the quantity of land-cover types but also its patterns differ significantly with parcel size (Robinson, 2012). Theobald (2001) found that impervious features cover up to 60 percent of land within parcels at high residential density area (more than one patch of impervious surface per 2 acres), but the proportion of impervious surface declines rapidly in areas with lower residential density and is indistinguishable from nearby agricultural area.

Fine-scale land-cover data provide the opportunity to analyze the distinctive patterns and ecological effects of exurban sprawl at the parcel level for several reasons. First, although existing studies have shown the scattering pattern of exurban sprawl at the county or regional level (Compas, 2007; Robinson, 2005), low resolution data or pixel-based classification of land-cover types alone cannot fully

capture the changes of land-cover patterns within residential parcels (Blaschke, 2010). Studies have found that the area of exurban settlements derived from classified satellite imagery is substantially underestimated, because the impervious surface occupies a small area and has a low spatial density, and thus likely to be classified as the nearby dominant land use, and other land covers within the large boundaries of exurban residential parcels are likely to be classified as non-residential use (Ridd, 1995; Theobald, 2001).

Second, the parcel is the areal unit at which land-cover decisions and land-management strategies are made by land owners and other stakeholders (Evans and Kelley, 2004; Theobald, 2005). Results have found that land management varies with land-use type and parcel size, even when parcels have similar land covers (Brown et al., 2005a; Irwin and Bockstael, 2007). For instance, residential parcels are expected to have more regular land management than undeveloped parcels, such as irrigation, fertilization, leaf litter removal, and addition of herbicides and pesticides. In contrast, parcels with fewer anthropogenic activities will exhibit a different condition of ecological process and nutrient exchange.

Additionally, within residential parcels, residents prefer different landscape designs, which consist of diverse proportions of land covers (i.e. mown turfgrass, shrubs, and trees) and demand different degrees of land management (Nassauer et al., 2009). In other words, the differences in land management will lead to different ecological consequences (Alberti, 2008; Forman, 2008; Heimlich and Anderson, 2001; Robinson et al., in press; Termorshuizen and Opdam, 2009), e.g., habitat disturbance, biodiversity, soil quality, carbon and water flux. In addition to ecological processes, land-cover patterns at the parcel-level also show linkages to various socioeconomic indicators (e.g., the relationship between measure of percent open space, land use diversity and fragmentation with housing price (Geoghegan et al., 1997); the relationship between vegetation richness and medium family income at the neighborhood level (Martin et al., 2004); the relationship between tree and impervious covers with household income and population density (Iverson and Cook, 2000; Talarchek, 1990) and the relationship between tree cover and tree species in within

parcel with resident's cultural background (Fraser and Kenney, 2000)), shared land-management strategies (Lambin et al., 2003) and aesthetic levels (Wu et al., 2004). Therefore, evaluating the land-cover dynamics within parcels may provide insightful information for bottom-up simulation that links landowners or developers' decisions on land cover and land management with ecosystem functions and consequences (Robinson et al., in press).

Third, the temporal change of land-cover patterns at parcel level can shed light on neighborhood effects and path dependence of land conversion. Based on an online survey, Nassauer and colleagues (2009) found that homeowners prefer to buy a house with a front yard design that is consistent with neighborhood appearance. However, these stated preferences still need to be confirmed by carefully examining the real dynamic of land cover pattern within residential parcels. In a separate study of the same region, An et al. (2010) reported that the timing and driving forces for exurban residential development vary by the type of development. They suggested that developers have a large influence on the neighborhood landscape and the timing of development. Hence, the collective influences of neighborhood effects and path dependency of development require investigation retrieved from parcel-level or sub-parcel level data (e.g., multiple land management units within a parcel).

The results presented by this chapter aim to shed light on our understanding of temporal changes in the quantity and pattern of land covers in exurban residential parcels at the urban-rural fringe in the following ways. First, this study provides an attempt to analyze temporal land-cover changes within exurban residential parcels. The results can be further used by non-stationary and bottom-up approaches for spatial analyses and simulation, such as survival analysis (An et al., 2010), duration modeling (Irwin et al., 2003) and agent-based modeling (Evans et al., 2001). Second, the results can be used to link the pattern and process at micro level and provide an opportunity to investigate the consequences of land-cover changes in exurban residential parcels, for instance, their impacts on carbon release, habitat fragmentation, biodiversity, and housing/parcel prices. Third, the findings can be used to verify the neighborhood effects suggested by stated preference surveys (Nassauer et

al., 2009) and to explore the process of the neighborhood effects brought by new residents (or developers) and existing residents.

Building on the findings and data used in a previous paper (Robinson, 2012), this chapter examines the temporal changes in exurban land-cover composition and configuration at the parcel and parcel-neighborhood level. To address this overarching goal, three specific questions are addressed: (1) How are land-cover composition and configuration altered at the parcel level during the period 1960 to 2000 in the exurban areas of Southeastern Michigan? (2) Is the land-cover pattern of an individual parcel consistent with the neighborhood appearance over time? And (3) is it possible to identify representative parcels that have experienced a convergence process³, in which land-cover quantities and/or patterns in exurban residential parcels conform the neighborhood appearance?

The rest of this chapter is organized as follows. Section 3.2 begins with an introduction of the study area and a general description of the land-cover data. Then, the methods of analysis of temporal changes of land-cover patterns and local spatial autocorrelation, and identification of representative parcels that are similar to their neighbors are explained in detail in section 3.3. In section 3.4, we report our findings on the three research questions respectively. Finally, general conclusions are summarized in section 3.5, and the potential implications and limitations of this study are discussed.

3.2 Study Area and data

3.2.1 Study area

The analysis was implemented in three townships, Pittsfield, Ray and Scio Townships, in Southeastern Michigan, which have undergone a pronounced exurban

³ The convergence is defined as land-cover quantities and/or patterns in exurban residential parcels conform the neighborhood appearance, as measured by the increase of the averages of local Moran's I for landscape metrics.

sprawl from 1960 on (Brown, 2003). In 1960, the land use is primarily agrarian in the three townships. Ray township is located at rural area of the city of Detroit, while Pittsfield and Scio are located at the urban-rural fringe of the cities of Ann. They have witnessed a transition from primarily agricultural use in 1960 to residential use in 2000 (see Figure 3-1).

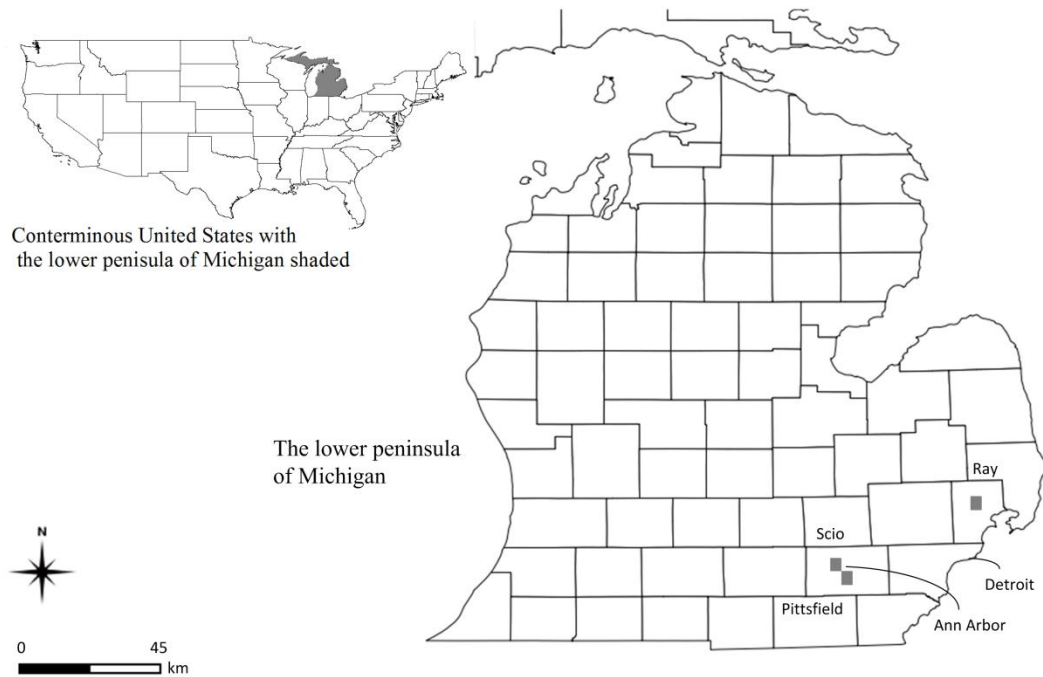


Figure 3-1 Location map of the study area

3.2.2 Data

Longitudinal and cross-sectional land-cover and parcel maps are collected by a previous study (Robinson, 2012). Parcels classified as single-family residential and not connected to urban infrastructure, such as a sewer system, were selected for the sample (see Figure 3-2). Due to the lack of archived historical parcel boundary data, a visual interpretation process was used to retrieve historical data from the original data in 2003. The process extracts residential parcels that do not change their size, shape, or land-use status in earlier dates. Parcels that are divided or merged over time were removed. Seven types of land cover (i.e. tree cover, open fields, maintained lawn, impervious structure, saturated areas, open water, cropland) were identified from

aerial photographs by manual interpretation and digitalized at decadal steps from approximately 1960 to 2000 at a minimum mapping unit of 10 meters. Parcel boundary data were obtained from corresponding counties in 2003. A more detailed explanation for the land cover and historical parcel creation methods and quality assessment is given elsewhere (Robinson, 2012).

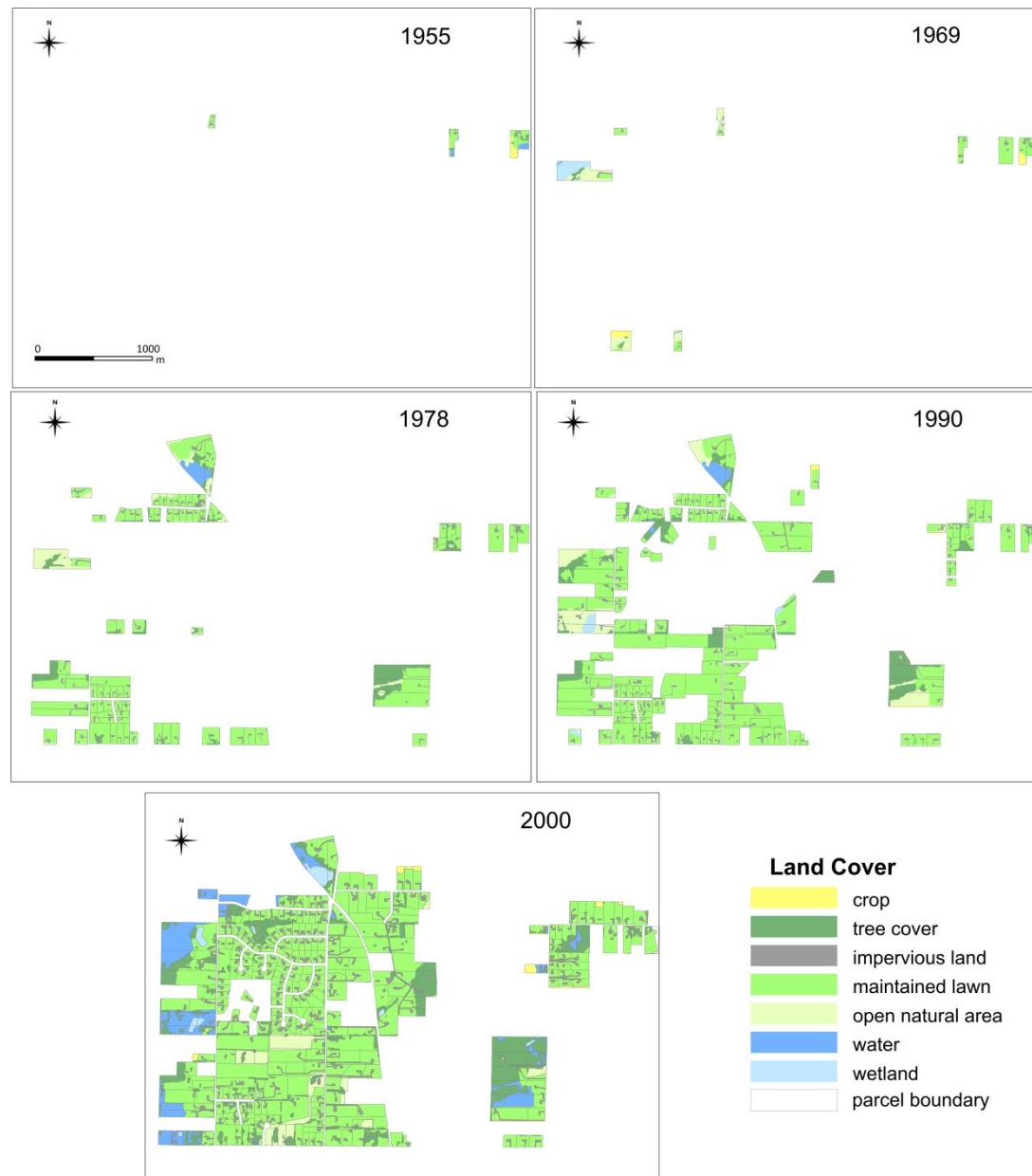


Figure 3-2 Residential parcels in a subarea of Pittsfield Township, Michigan, from year 1955 to 2000. Parcels shown are those developed prior to the reported date. The number of parcels will increase and land cover within parcels may change over time.

3.3 Methods

To address the three research questions, the spatiotemporal dynamics of land-cover patterns are measured by landscape metrics within each parcel (McGarigal et al., 2002). Consensus exists that a small set of landscape metrics is sufficient to capture the main characteristics of landscape pattern (Li and Wu, 2004; Wu et al., 2011). Based on these findings and the correlation among different metrics, five metrics were chosen by Robinson (2012, pg. 59-60) that describe “land-cover proportions and quantity (i.e., total land cover, TLC), edge characteristics (i.e., edge density, ED), degree of fragmentation (i.e., number of patches, NP and mean patch size, MPS), and shape (i.e., area weighted mean shape index, AWMSI)”. To maintain continuity and extend the analysis of land-cover change, this chapter uses these same metrics. The functions for each landscape metric (McGarigal et al., 2002) are given below:

$$ED = \frac{E}{TLC} \quad (3-1)$$

$$MPS = \frac{TLC}{NP} \quad (3-2)$$

$$AWMSI = \sum_i \left(\frac{p_i}{2\sqrt{\pi \times a_i}} \times \frac{a_i}{\sum_i a_i} \right) \quad (3-3)$$

where, E stands for total length of edges for a land-cover type, p_i and a_i are perimeter and area of the i th patch for a land-cover type respectively. ED varies from 0 to 4 in a raster division of space. In this context, consistent with the previous study (Robinson, 2012), we assume that parcels with higher value of ED suggest more fragmented patterns and vice versa. AWMSI is 1 when the patch is most compact (i.e., a square in a raster division of space) and will increase when the geometric shape is distorted.

To assess the temporal change in land-cover composition and configuration in residential parcels from 1960 to 2000 (i.e. research question 1), each parcel was attributed with the following information: (1) timing of development (e.g., before 1960s, between 1970 to 1980), (2) parcel size, and (3) five landscape metrics calculated for four main land-cover types (i.e. tree cover, open fields, maintained

lawn, impervious structure) in each available time period. Landscape metrics for the other three land-cover types (i.e. saturated areas, open water, cropland) were excluded because the three land-cover types are not common features found in exurban residential parcels. Results were stratified by parcel size to coincide with previous work (Robinson, 2012).

To examine the neighborhood effects on the quantity and pattern of land covers in nearby residential parcels (i.e. research question 2), one of the local indicators of spatial association (LISA), local *Moran's I* (LMI)⁴, is used to measure spatial similarity of landscape metrics (Anselin et al., 2006). The LMI can be calculated as below:

$$LMI = \frac{z_i}{\sum_j w_{i,j}} (z_i - \bar{z}) \quad (3-4)$$

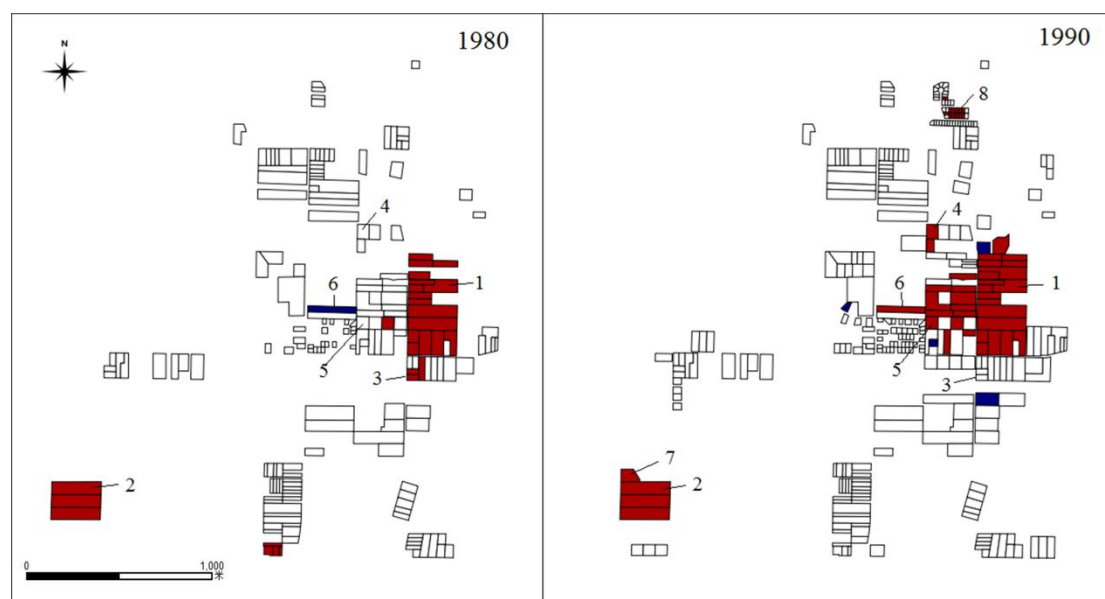
where z_i is the value of a landscape metric in a parcel i , $w_{i,j}$ stands for the neighborhood weight matrix and \bar{z} denotes the mean value of the landscape metric in the neighborhood. In this study, the LMIs across landscape metrics of land-cover types are calculated for all parcels at each time period, using the first order Queen's case of neighborhood design (i.e., nearest 8 neighbors in raster division). Values of LMI range from -1 to 1. For each landscape metric, a -1 value of LMI indicates the values of that metric in a neighborhood are completely different, while a 1 value suggests they are identical. A zero value indicates the values of that metric are randomly distributed in the neighborhood. The changes in the average values of LMI for all the parcels can reflect the spatial similarity of landscape metrics in the neighborhood globally.

However, the reasons for the observed changes of average LMIs are complex

4 Both local Moran's I and local Geary's C are indicators of spatial autocorrelation. The equation of local Geary's C (LGC) is: $LGC = \frac{\sum_j w_{i,j} (z_i - z_j)^2}{\sum_j w_{i,j}}$. The values of LGC vary from 0 to 2. A 1 value means there is no spatial autocorrelation. Values higher than 1 mean increasing negative spatial autocorrelation, whilst values lower than 1 illustrate increasing positive spatial autocorrelation. LGC is inversely related to LMI. I choose LMI because it can be calculated by GeoDa and its significance can be tested in Geoda (Anselin et al., 2006).

as the values of LMI depend on both the number of neighbors and the degree of spatial autocorrelation. For a given parcel, it may gain new neighbors over time; meanwhile its own and/or its neighbors' land-cover composition and configuration may change. Collectively, it is difficult to trace the reasons for the changes of average LMIs. Therefore, additional approaches are implemented to identify representative parcels that adopt similar land-cover patterns to their neighbors (i.e. research question 3).

The cluster index (CI), another LISA statistic, can be used to identify parcels that are significantly similar to their neighbors ([Anselin, 1995](#)). The cluster index is a by-product of the significance test of LMI. It tests the significance of LMI by a conditional randomization process, in which the values (in this case, landscape metric values) in the neighborhood are permuted 10,000 times ([Anselin, 1995](#)). For a parcel, the value of CI can divide LMIs into three categories: not significant (category I), significantly similar (category II) and significantly dissimilar (category III) (as illustrated in Figure 3-3). Since the aim is to identify representative parcels that have similar land-cover patterns to their neighbors, we focus on the parcels in category II, in which their landscape metrics are significantly similar to their neighbors. Meanwhile, for each period, we divide the parcels into two sets. One consists of newly developed parcels (hereafter referred to as the “New” parcels) in each period and the other is composed of parcels already developed (hereafter referred to as the “Old” parcels) in that period.



Categories	Color	Meaning in the study
I	White	The value of a landscape metric in a parcel isn't significantly similar or dissimilar to the values in the neighborhood ($p > 0.05$).
II	Red	The value of a landscape metric in a parcel is significantly similar to the values in the neighborhood ($p < 0.05$).
III	Blue	The value of a landscape metric in a parcel is significantly dissimilar to the values in the neighborhood ($p < 0.05$).

Figure 3-3 Temporal change of the three categories of LMIs by cluster index for a landscape metric in a sample area of Pittsfield from 1980 to 1990 (parcel # 1 and 2 are Old parcels that remained in category II; parcel # 3 is an Old parcel changing from category II to category I; parcel # 4 to # 6 are Old parcels changing from category I and III to category II respectively; and parcel # 7 and 8 are New parcels added in 1990 and belonging to category II).

For each landscape metric, the temporal change of the number of parcels belonging to category II (N) can indicate whether there are more parcels having similar values of that landscape metric over time. For a specific time period, several processes may affect the temporal changes of N (see the examples in Figure 3-3): (1) the number of Old parcels remaining in category II from a previous period to this period (parcel # 1 and 2 in Figure 3-3); (2) the number of Old parcels that change from category II in a previous period to category I or III in this period (parcel # 3 in Figure 3-3); (3) the number of Old parcel that change from category I or III in a previous period to category II in this period (parcel # 4 to 6 in Figure 3-3); and (4) the

number of New parcels belonging to category II that are added in the period (parcel # 7 and 8 in Figure 3-3). In such a way, we are able to find out whether the Old parcels or the New parcel contribute to the change of N.

3.4 Result analysis

3.4.1 Parcel distribution

Results show that the last four decades witnessed an extensive amount of exurban residential development (Table 3-1). The total number of residential parcels increased more than tenfold within our study area. Similarly, the total parcel area classified as exurban residential increased nearly 15 times. Collectively, over the same period of time, the average parcel size also increased by 16.25% from 1.98 acres to 2.30 acres.

Table 3-1 Main characteristics of residential parcels from 1960 to 2000

	Total number of parcels	Total land cover (acres)	Average parcel size (acres)	Standard deviation of parcel size (acres)
1960	348	687.37	1.98	2.32
1970	1065	1964.38	1.84	2.22
1980	1633	3437.80	2.11	2.58
1990	2829	6467.50	2.29	2.82
2000	4464	10250.56	2.30	3.06

Despite the rapid expansion of area classified as exurban development, the distribution of parcel sizes only have minor changes in 1970 and remain relatively stable in the other decades observed (Figure 3-4). A large proportion of parcels (about 75%) have a parcel size below the average parcel size (smaller than 2 acres, see Table 3-1). Among the nine levels of parcel size, parcels with a size from 0 to 1 acres account for the largest proportion. Less than 20% of all the parcels have a size larger than 4 acres.

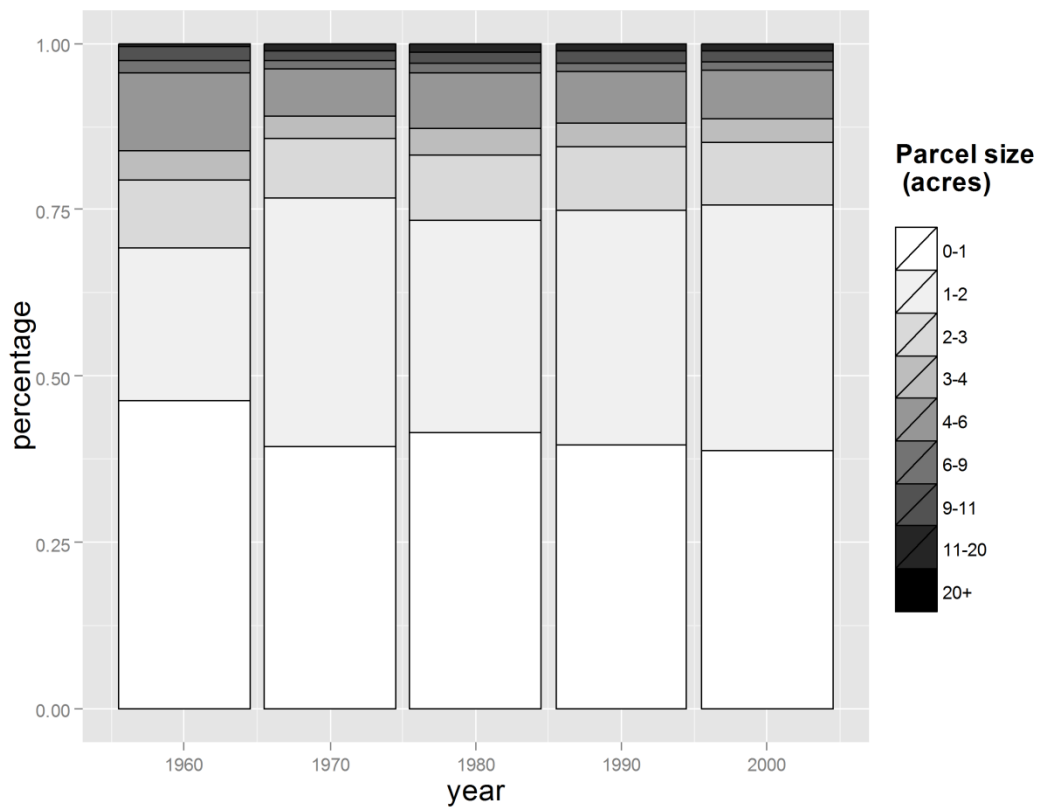


Figure 3-4 Distribution of parcels stratified by 9 levels of parcel size from 1960 to 2000

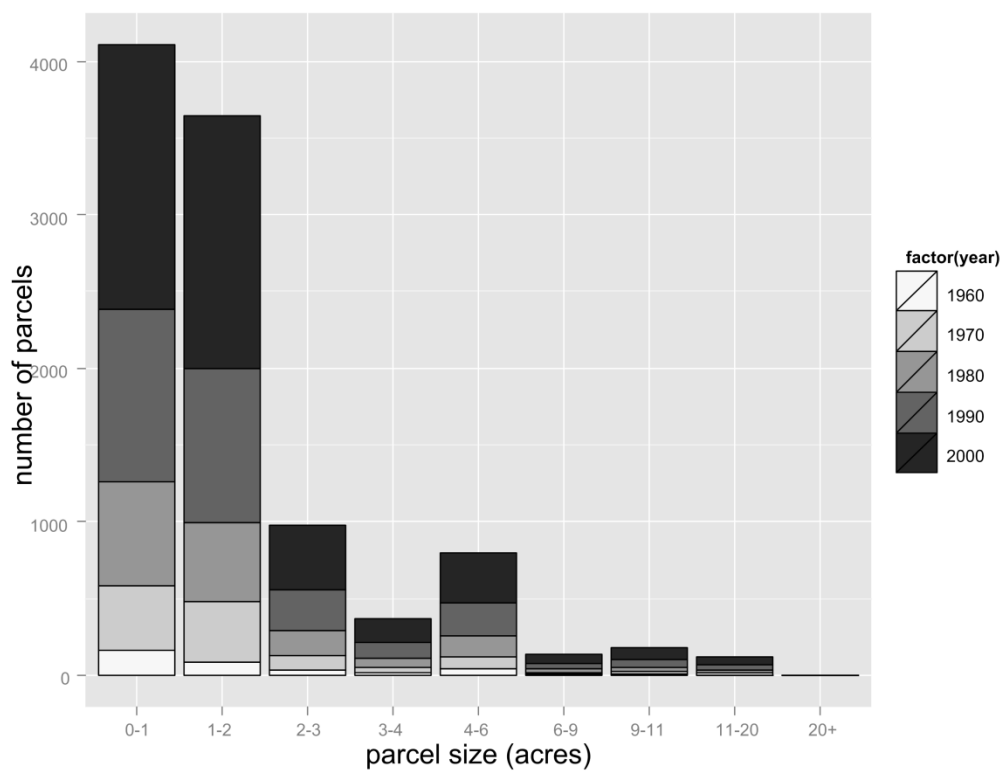


Figure 3-5 Number of parcels grouped by parcel size from 1960 to 2000

In terms of the growth in the number of exurban residential parcels grouped by parcel size (shown in Figure 3-5), invariably, the number of parcels in each bin of parcel size increased over time. Parcels with a size smaller than 2 acres (i.e., the first two bins) outnumbered other levels of parcel size prominently. As indicated by the pervious study (Robinson, 2012), the quantity and pattern of land-cover types significantly differ with parcel size, so it is necessary to keep in mind that the large amount of small size parcels will have a predominant influence on the average values of landscape metrics.

3.4.2 Temporal patterns of land cover

The quantity and pattern of each land cover show some distinctive features. Table 3-2 reports the average value of each landscape metric among all the residential parcels for four land-cover types. The average area of tree cover and the average number of patches of tree cover increased steadily over the four decades, as indicated by the increases in average TLC and NP in Table 3-2. The standard deviations of NP for tree cover are the largest among the four land-cover types, which implies a diversity in number of tree-cover patches in exurban residential parcels. The values of ED and AWMSI also increased over time, except a slight decrease in ED from 1980 to 1990. This indicates that the distribution of tree-cover patches became more fragmented and the shape of tree-cover patches became more irregular. These changes may be explained by multiple factors, for instance, growth of trees around the edges of patches, and/or establishments of new growth areas for trees.

Average area of impervious structure had a moderate increase over time with a decline in 1970. The average number of patches fluctuated between 1.0 and 1.3, which combined with small standard deviations of NP suggests that most parcels have only one patch of impervious structure. This is consistent with the previous result that majority of parcels are in small size and thus have only one patch of impervious structure. The slightly higher average patch number can come from large parcels

which may have additional patches of impervious structure (e.g., separate storage buildings).

Table 3-2 Summary statistics for landscape metrics for the four land-cover types from 1960 to 2000

	TLC (m ²)		NP		MPS (m ²)		ED		AWMSI	
	mean	SD	mean	SD	mean	SD	mean	SD	mean	SD
Tree cover										
1960	1649.04	3553.66	1.36	1.34	1025.13	2115.60	0.23	0.36	1.19	0.81
1970	1809.97	4498.21	1.32	1.38	1048.93	2461.79	0.33	1.26	1.24	0.91
1980	2292.81	4894.36	1.44	1.29	1555.12	3686.41	0.33	1.42	1.41	0.89
1990	3051.88	6568.96	1.59	1.45	2034.42	4700.88	0.31	1.29	1.48	0.92
2000	3100.42	7217.01	1.64	1.61	1907.15	5208.56	0.33	1.95	1.48	1.01
Impervious structure										
1960	652.93	502.39	1.24	0.67	555.68	420.22	0.35	1.01	1.77	0.58
1970	598.87	359.50	1.04	0.36	573.60	353.03	0.34	1.13	1.83	0.69
1980	658.91	434.64	1.05	0.34	627.25	417.30	0.35	1.16	1.94	0.80
1990	666.06	441.56	1.36	0.89	552.88	395.19	0.38	1.09	2.01	0.87
2000	714.36	573.98	1.10	0.43	658.77	546.88	0.35	1.17	1.96	0.83
Maintained lawn										
1960	2609.96	3235.45	1.30	0.80	2029.31	2770.01	0.21	0.61	1.64	0.72
1970	3073.24	3221.55	1.25	0.76	2598.31	2991.39	0.16	0.32	1.69	0.65
1980	3456.52	4140.50	1.29	0.76	2877.64	3649.00	0.21	1.08	1.68	0.67
1990	3553.09	4731.67	1.48	1.03	2683.12	3915.92	0.21	0.92	1.67	0.71
2000	3310.66	4240.52	1.41	0.90	2617.89	3591.32	0.26	3.37	1.78	0.69
Open fields										
1960	1064.34	4772.73	0.21	0.48	903.09	4088.97	0.04	0.16	0.34	0.80
1970	698.01	3124.91	0.21	0.58	563.99	2703.62	0.25	4.16	0.34	0.90
1980	1088.26	4406.25	0.27	0.60	893.52	3809.89	0.13	0.86	0.44	1.00
1990	672.21	3575.98	0.18	0.62	463.73	2741.81	0.08	0.74	0.24	0.81
2000	1351.45	5089.58	0.33	0.79	1000.94	3920.33	0.24	2.48	0.45	0.93

Compared to the other three land-cover types, on average, maintained lawn occupied the largest amount of area across all parcels. The average TLC of maintained lawn increased from 1960 to 1990 but decreased slightly after 1990. Like impervious structure, the average number of patches of maintained lawn fluctuated between 1.25 and 1.48 because exurban residential parcels usually have one to two patches of maintained lawn (e.g., a front yard and a back yard).

By definition, open fields constituted areas that consisted of tall-grass prairie, unmanaged turfgrass or other grasses, or other natural areas not identifiable as

maintained lawn or tree cover. Partly because of this “catch all” category and because it acts as a transition zone between managed and unmanaged land as well as between maintained lawn and tree cover, partly because not every parcel has open fields, no metric showed an observable trend over time for open fields. Therefore, the average values of the five landscape metrics fluctuate in this land cover, as indicated by the large values in standard deviations of TLC and MPS.

In summary, multiple factors influence the average values of landscape metrics over time. First, they are affected by the distribution of parcel size. The results show that the majority of small size parcels have a great influence on the average values of metrics. Second, they are also affected by the differences in characteristics of land-cover quantity and pattern among parcel sizes. For instance, the standard deviation of a given metric will be much lower if the metric remains relatively stable among different parcel sizes rather than increases with parcel size.

3.4.3 Temporal dynamic of spatial autocorrelation

To investigate temporal change of spatial autocorrelations of metrics, local Moran’s I (LMI) are calculated for each metric of the four main land-cover types. Average LMIs (parcels that do not have neighbor in the defined neighborhood are excluded in the calculation of the average values) for each landscape metrics of land covers are depicted in Figure 3-6.

Results for average LMIs suggest that some convergence of land-cover patterns within neighborhoods (as indicated by the increase of average LMIs) occurs between 1980 and 2000. The mean values of LMI for almost all metrics except ED for the three major land covers (except open fields) increased in the time period between 1980 and 2000. This convergence is not seen in 1960 and 1970 for different reasons.

In 1960, the average LMIs for some metrics (e.g., MPS of tree cover and maintained lawn) are large (greater than the values in 2000), due to a small sample size (Table 3-2). The small sample size results from a small number of parcels (i.e., 348) that are predominantly isolated and dispersed across space, which excludes most

from our LMI calculations because of the lack of neighbors. Thus, the mean values of LMI only account for a small sample of parcels which may have prominently large LMIs.

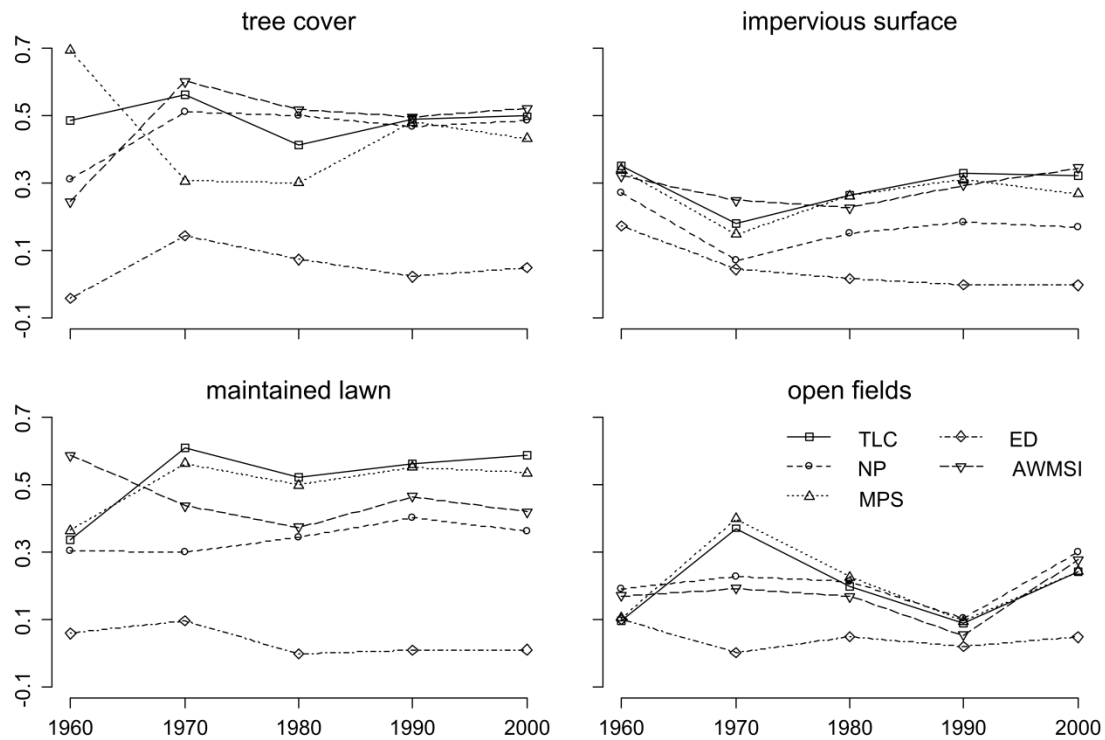


Figure 3-6 Temporal dynamic of average local Moran's I for the four land cover types from 1960 to 2000.

In 1970, there are spikes and dips in the average values of LMI for most metrics of tree cover, impervious structure and maintained lawn. These spikes and dips reconfirm previous findings that the dominant parcel size has impacts on the quantity and pattern of land-cover types. As illustrated in Figure 3-4, in comparison to the other four time periods, there are many more parcels with a size between 1 to 2 acres and fewer parcels with a size between 4 and 6 acres in 1970. It means the influence of small size parcels is in its highest in 1970. Combined with previous findings (Robinson, 2012) that the metrics for tree cover and maintained lawn differ significantly with parcel size, it is logical to infer that in 1970 the spatial autocorrelation will increase because the majority of parcels are small size parcels with similar metric values. In contrast, with regard to impervious surface, the same

study (Robinson, 2012) found the metrics remain relatively consistent among parcel size. Therefore, the spatial autocorrelation does not increase in 1970.

Similar reasons may explain the increasing trend of average LMI from 1980 to 2000. First, the distribution of parcels grouped by their sizes remains relatively stable from 1980 to 2000 (see Figure 3-4). In other words, the dominant parcels are small size parcels. They may lead to the increase in spatial autocorrelation. In addition, parcels may have more neighbors as some new parcels are developed around existing ones.

As illustrated in the previous section, the metrics for open fields fluctuate over time. Therefore, the LMIs also exhibit a fluctuating trend over time. For the fragmentation of patches indicated by ED, LMIs for the four land covers are relatively low and close to zero. This indicates a random spatial distribution of fragmentation. The result is consistent with the result in Table 3-2 that the standard deviations of ED for the four land covers are relatively large.

In summary, we found some evidence that the quantity and pattern of three major land covers (i.e. tree cover, impervious structure, and maintain lawn) in exurban residential parcels become more spatially similar over time. The reason for the conformity in the neighborhood may arise from multiple factors because the value of LMI for a specific parcel depends both on the number of neighbors as well as their metric values. However, it is difficult to identify parcels that change their land-cover composition and configuration to conform neighborhood appearance from the increases in average values of LMI. The identification of parcels that are gradually becoming similar to their neighbors is investigated in the next section.

3.4.4 Identification of parcels conforming to their neighbors

Based on the results of the cluster index (CI) explained in the Methods section, there are an increasing number of parcels that are significantly similar to their neighbors

over time. From Table 3-3, this trend can be found for all the three major land-cover types (Open fields are excluded in this section because, as found in previous section, there is no obvious convergence of patterns occurring over time). For each period, the total number of parcels that are significantly similar to their neighbors identified by the cluster index can come from three subsets of parcels. The first subset (Subset I) consists of the Old parcels that remain significantly similar to their neighbors from the previous period to current period. The second (Subset II) is composed of the Old parcels that change from not significant or significantly different in the previous period to significantly similar in current period. And the third (Subset III) are the New parcels in current period that are significantly similar to their neighbors. The number for each subset is also recorded in Table 3-3 over time.

The main source for the increase in the number of parcels that are significantly similar to their neighbors comes from the New parcels. For most landscape metrics, the percentage of Subset III (the New parcels) exceed the percentage of the other two subsets substantially from 1970 to 1990, and are still large in 2000. These New parcels may be developed around Old parcels and adopt similar land-cover patterns (parcel # 7 in Figure 3-3 is an example) to the Old ones, or they may be created in a new subdivision with other New parcels that have similar land-cover patterns (parcel # 8 in Figure 3-3).

The Old parcels also contribute to the increasing number of parcels that are significantly similar to their neighbors. Over time, the number and percentage of parcels that remain similar to their neighbors increased steadily and exceed the number of the New parcel (Subset III) in 2000. These Old parcels take up a large proportion of the total number of parcels that are similar to their neighbors in the previous period (e.g., for TLC of tree cover, there are 67 out of 95 (70.53%) parcels remaining significantly similar to their neighbors from 1970 to 1980. The percentages in 1990 and 2000 are 53.54% (121/226) 75.97% (313/412) respectively, see Table 3-3). Combined with the result that the New parcel are main source for the increase in total number of significantly similar parcels, it suggests a large proportion of the New parcel that are similar to their neighbor may retain the similarity in a later period.

Table 3-3 Temporal change of number and percentage of parcels that are significantly similar to their neighbors for three major land-cover types
(percentages of each subset are reported in rows marked by “%”)

		Tree cover					Impervious structure					Maintained lawn				
		TLC	NP	MPS	ED	AWMSI	TLC	NP	MPS	ED	AWMSI	TLC	NP	MPS	ED	AWMSI
1970	Subset I	7	1	6	2	3	3	5	0	2	5	9	7	8	5	8
	%	8.75	1.39	8.57	3.13	3.66	6.52	6.49	0.00	9.09	11.63	15.79	43.75	13.11	20.00	18.18
	Subset II	8	14	9	3	14	11	23	17	13	16	24	12	23	17	21
	%	10.00	19.44	12.86	4.69	17.07	23.91	29.87	38.64	59.09	37.21	42.11	75.00	37.70	68.00	47.73
	Subset III	80	72	70	64	82	46	77	44	22	43	57	16	61	25	44
	%	84.21	82.76	82.35	92.75	82.83	76.67	73.33	72.13	59.46	67.19	63.33	45.71	66.30	53.19	60.27
Total		95	87	85	69	99	60	105	61	37	64	90	35	92	47	73
1980	Subset I	67	43	55	24	38	16	12	15	8	21	45	18	42	21	31
	%	29.65	26.38	26.70	20.34	18.72	14.41	12.90	13.89	9.76	18.92	26.32	21.69	22.83	27.27	23.31
	Subset II	59	56	54	42	75	46	43	44	41	41	53	38	56	37	60
	%	26.11	34.36	26.21	35.59	36.95	41.44	46.24	40.74	50.00	36.94	30.99	45.78	30.43	48.05	45.11
	Subset III	100	64	97	52	90	49	38	49	33	49	73	27	86	19	42
	%	44.25	39.26	47.09	44.07	44.33	44.14	40.86	45.37	40.24	44.14	42.69	32.53	46.74	24.68	31.58
Total		226	163	206	118	203	111	93	108	82	111	171	83	184	77	133
1990	Subset I	121	36	120	28	78	57	9	46	18	42	119	43	127	35	74
	%	29.37	15.38	30.53	13.73	23.28	19.59	8.91	17.56	13.74	17.95	27.36	21.29	28.41	17.59	24.92
	Subset II	72	84	80	57	83	94	53	88	47	69	120	88	125	68	118
	%	17.48	35.90	20.36	27.94	24.78	32.30	52.48	33.59	35.88	29.49	27.59	43.56	27.96	34.17	39.73
	Subset III	219	114	193	119	174	140	39	128	66	123	196	71	195	96	105
	%	53.16	48.72	49.11	58.33	51.94	48.11	38.61	48.85	50.38	52.56	45.06	35.15	43.62	48.24	35.35
Total		412	234	393	204	335	291	101	262	131	234	435	202	447	199	297
2000	Subset I	313	126	292	101	194	160	30	126	41	125	279	95	288	103	162
	%	53.16	48.72	49.11	58.33	51.94	48.11	38.61	48.85	50.38	52.56	45.06	35.15	43.62	48.24	35.35

Subset II	142	197	139	114	223	208	73	190	124	196	176	136	182	176	182
	22.33	45.81	23.40	36.19	36.98	36.36	51.05	39.58	47.15	39.44	23.75	44.74	23.92	39.73	36.25
Subset III	181	107	163	100	186	204	40	164	98	176	286	73	291	164	158
	28.46	24.88	27.44	31.75	30.85	35.66	27.97	34.17	37.26	35.41	38.60	24.01	38.24	37.02	31.47
Total	636	430	594	315	603	572	143	480	263	497	741	304	761	443	502

Note: Subset I: parcels remain significantly similar from the previous period to current period; Subset II: parcels change from not significant or significantly different in the previous period to significantly similar in current period; Subset III: new developed parcel in current period which are significantly similar to their neighbors.

The number in Subset II (the Old parcels that change from not significant or significantly different to significantly similar) also increased over time. Possible processes include (but are not limited to): a new neighbor is developed around the Old parcel and the Old one becomes similar to its neighborhood (parcel # 4 in Figure 3-3); an Old parcel becomes similar to its neighbors even though there is no new parcel developed in its neighborhood (parcel # 5 in Figure 3-3); an Old parcel changes from significantly different to significantly similar in a later period (parcel # 6 in Figure 3-3).

3.5 Discussion and Conclusion

3.5.1 Summary

Based on a land-cover dataset in exurban area of Southeastern Michigan, we analyzed land-cover evolution from the parcel perspective. The results show that, from 1960 to 2000, the number and amount of area classified as exurban residential parcels increased steadily over time. The distribution of parcels with different sizes for the five periods (i.e., 1960, 1970, 1980, 1990 and 2000) experienced minor changes over time. The number of parcels close to 1 acre showed the greatest increase among all parcel sizes, while parcels with a size larger than 6 acres experienced the slowest growth in numbers.

The temporal change of quantity and pattern of land cover for the four types observed (i.e., tree cover, impervious structure, maintained lawn and open fields) were distinct. Specifically, more tree cover is found within parcels over time but with a more fragmented and irregular composition. Most parcels have only one patch of impervious structure with a relatively stable acreage and fragmentation over time. On average, maintained lawn has the largest total land cover compared to the other three land-cover types. The values of landscape metrics for open fields are less regular and have larger values of standard deviations than the other land-cover types. That is because mostly only parcels with a relatively large size have open fields. Combined with previous findings

that land-cover composition and configuration may differ significantly with parcel size (Robinson, 2012), we find the average patterns of land cover across all parcels are affected by the parcel size that shares the dominant proportion in the total number of parcels. Specifically, in the study area, the majority of parcels are small in size, and their land-cover patterns influence the average patterns substantially. More discussion about the effect of parcel size can be found in the section about future work (see Section 3.5.3).

In addition to the dynamics of landscape metrics for the four land-cover types, we also analyzed the spatial autocorrelation of these metrics using local Moran's I. The results reveal that, except for open fields, the similarities of most landscape metrics in the neighborhood for the three major land-cover types (i.e. tree cover, impervious structure and maintained lawn) increased over time with some small fluctuations. This implies that the land-cover patterns have a convergent trend among the neighboring parcels.

Using the cluster index, we are able to identify parcels that are significantly similar to their neighbors. Over time, the number of these parcels increased steadily. The New parcels developed in each period account for a large proportion of the total number of these parcels, while the Old parcels that change from not significant or significantly different to significantly similar also contribute to the increase in the number of these parcels. The results also support the convergence on the quantity and pattern of land cover in the neighborhood.

3.5.2 Implications and potential

The findings in this study have additional implications for (1) the ecological consequences of exurban development, (2) the social influences of neighborhood effects and (3) policy design. First, understanding the dynamic of land-cover patterns within parcels is the first step toward linking exurban land-cover change with its ecological consequences. In our study, the number and areas of residential parcels increased steadily over time. Compared to development in urban areas, these exurban parcels covers a larger

amount of land, and share the features of low density of impervious structure and large parcel size. This suggests, in contrast to the severe impact limited to a small area caused by the compact development in urban areas, exurban development will have a more spatially extensive ecological impact. For example, a comparison of effects on biodiversity between compact urban development and sprawling exurban development found that both types of development reduce overall bird distribution spatially (Sushinsky et al., 2012). In addition, the urban-sensitive species benefit from compact development because of the intact large green space, while the non-native species increase along the sprawling development.

In addition, land cover in exurban residential parcels is also different from original natural land cover in exurban area. We found that, in the study area from 1960 to 2000, the majority of parcels are parcels with a relative small size (Figure 3-5). It may be the case that these small parcels are from a residential subdivision developed by a developer with similar land-cover patterns. Commonly, the landscape design in these parcels consists of impervious structure, maintained lawn and tree cover. The anthropogenic activities invested in these land covers are significantly different from natural surfaces in terms of chemical inputs, supplies of water and energy, and disturbances of wildlife habitat. For example, maintained lawn, which has the largest average land cover within residential parcels in our study (Table 3-2), requires continued inputs in petrochemicals, fertilizers, pesticides, irrigation and periodic removal of litter. It will influence carbon storage and nutrient cycles between vegetation and soil. It has been found that inputs of fertilizers and pesticides will increase the risk of water quality deterioration and loss of biodiversity (Robbins and Birkenholtz, 2003). A simulation coupled by an agent-based model and the ecological process model BIOME-BGC developed for the same study location also confirms that variations of land management (addition versus removal) on turfgrass and dense tree cover in exurban parcels will have substantial effect on carbon storage (Robinson et al., in press). In other words, the

management of the reported land covers can change the quality of the ecosystem function. Analysis of this topic is beyond the scope of this chapter but this chapter hopes to provide a foundation for just this sort of work.

Second, measuring land cover evolution and similarity in the neighborhood in exurban areas has paved the path to understand the relationship between land-cover patterns and process of land-cover convergence. The results show that average spatial autocorrelation among land-cover metrics increased from 1980 to 2000, and newly developed parcels are main source for the number of parcels that are significantly similar to their neighbors. As suggested by a previous study in the same study area (Nassauer et al., 2009), the reason for the convergence is that parcels may imitate their neighbors' landscape designs, which leads to the increase in average LMIs. In addition to imitation, alternative drivers can result in the convergence, such as multiple parcels developed by a single developer in a subdivision, aging of vegetation on the property, and restrictions on yard design established by local communities.

However, not all the parcels follow the convergence process, because the land-cover designs within parcels are not only influenced by demographic and cultural characteristics of households, but also restricted by physical conditions of houses and environment. These factors include income level and construction year of house (Robbins and Birkenholtz, 2003), origin of households (natives versus domestic migrants), policy restrictions imposed by neighborhood associations (Martin et al., 2003), appearance and maintenance of yards, microclimate, health and safety concerns (Larson et al., 2009), and cultural background (Fraser and Kenney, 2000; Rishbeth, 2004). Thus, the preferences and drivers for individual residents can differ greatly.

Third, enhanced understanding of ecological consequences and neighborhood effects will play an important role in guiding and designing policies to encourage environment-friendly and sustainable land cover in exurban area. Researchers have found that the aesthetic expectations of households and enhancement of ecological quality can

be achieved simultaneously by adopting innovative designs (Nassauer et al., 2004). Therefore, it is possible to shift the landscape design toward one that sustains ecological functions and satisfies households' desire simultaneously. However, the policy and guidelines must be made carefully, as there are thresholds and limitations for an acceptable degree of changes. For example, Nassauer (1993) found that replacing more than 75% of turf area with a colorful range of prairie plants may not be acceptable, but it may be acceptable to replace 50%. In other words, some land-cover designs and land management activities can be changed by marketing and educational strategies, but some are rooted in households' basic demand and are hard to change.

In summary, the dataset containing temporal changes of land-cover patterns within residential parcels in exurban areas has great potential to explore a much broader research agenda. It can provide the distributions and patterns of managed land covers, which are hard to distinguish from natural land covers in remotely sensed images. It meets the data demand of bottom-up simulations, which require trajectories of land-cover changes within individual decision-makers' (e.g., household) jurisdiction, to drive, parameterize and verify the model. In addition, by linking this dataset with other datasets or models, it can explore a broad dimension of perplexing research questions, such as the ecological consequences of exurban development (Alberti, 2005), the relationship between landscape preferences and social and cultural norms (Nassauer, 1995), the influence of land-cover patterns on housing prices (Geoghegan et al., 1997; Kong et al., 2007; Song and Knaap, 2004a; Tyrväinen, 1997), and the verification of stated preferences on landscape design by surveys.

3.5.3 Limitations and future work

Although results in this chapter can work as a step towards better understanding causal relationships between processes of land-cover change and land-cover patterns, and between land-cover processes and consequences at the level of individual parcels, there

are some inevitable limitations and uncertainties that are worth exploring further in the future work. First, this empirical case only studied three townships in Southeastern Michigan. The results in this study cannot be uniformly applied to all the exurban development in the United States. For instance, the landscape design in arid environments (e.g., a desert city, Phoenix) can greatly vary from the design in the Midwest ([Larson et al., 2009](#)).

Second, it is difficult to interpret land-cover changes within exurban residential parcels because its land use is in the transition stage between highly man-made and completely natural. As discussed in section 3.4.1, open fields do not show an obvious trend in its landscape patterns because this land cover includes all the other land cover types that do not belong to the six land-cover types. Therefore, open fields include various land covers with different degrees of management (e.g., tall-grass prairie, unmanaged turfgrass or other grasses, or other natural areas not identifiable as maintained lawn or tree cover). This problem will be enhanced in the interpretation of land covers from aerial photos when an aerial photo is old and has shade.

Third, in this study, the spatial autocorrelation indicator, local Moran's I , is sensitive to both the value of landscape metric in the neighborhood and the number of neighbors. In other words, how to define the neighborhood and how to control the number of neighbors to guarantee the result of spatial autocorrelation comparable among parcels will need to be further investigated. In addition, although we are able to identify the increasing number of parcels that are significantly similar to their neighbors over time, the results are not enough to support the hypothesis that the convergence results from intentional imitations among neighbors. That is because other factors can also lead to the convergence, for example, local policies and restrictions that specify acceptable landscape designs within residential parcels. In other words, this study found some evidence of convergence of land-cover change at the neighborhood level from a statistical perspective rather than a behavioral perspective. A further investigation can be made by

surveying these convergent parcels that significantly similar to their neighbors on their intentions to the convergence.

Fourth, in this study, all parcel data is based the year 2003 parcel data layer, and parcels that changed in size because of aggregation or division are excluded in the dataset. It is impossible to know their effects on the average quantity and pattern of land-cover types within parcels and at the neighborhood level. In addition, although this study found that parcel size could have great influence on the average values of landscape metrics, a more thorough investigation that stratifies parcels by size and analyzes the temporal changes of quantity and pattern of land-cover for each category of parcel size is the next step to confirm the effect of parcel size.

Finally, the time interval for the land-cover change in the dataset is about 10 years; however, there is no information on the exact date when a parcel is developed or an old parcel is sold to a new resident. It is possible there are some parcels that are undergoing an intense transition of landscape design because of the ownership exchange, and some parcels that remain a stable landscape design after a long-term settlement. The analysis treats the two kinds of parcels within a time period the same and may influence the results. A further effort to distinguish the parcels between stable landscape patterns and dynamic landscape patterns within a time period can further enhance our understanding of temporal change of land-cover patterns within exurban residential parcels. This work can be done by tracing the transaction histories of parcels and corresponding land-cover change within parcels.

Chapter 4 A Review of Urban Residential Choice Models Using Agent-based Modeling

4.1 Introduction

In the field of urban land-use change simulation, a growing volume of literature is applying an agent-based modeling (ABM) approach to construct models, due to its ability to represent individual's decision-making process and mobility from the bottom up (An, 2012; Haase and Schwarz, 2009; Kennedy, 2012; Macy and Willer, 2002; Matthews et al., 2007; O'Sullivan et al., 2012; Parker et al., 2003; Torrens, 2012). Among a continuum from theoretical to empirical, at one end, purely theoretical and stylized models are developed to simulate classical urban residential phenomenon, such as monocentric patterns of cities and segregation of residents (e.g., Benenson and Torrens, 2004a; Crooks et al., 2008). At the other end, empirical models driven by extensive spatial and non-spatial data are constructed to simulate residential choices within a complex urban system (e.g., Birkin and Wu, 2012; Zaidi and Rake, 2001). Between the two extremes, a number of models, which are based partly on empirical situations and partly on theoretical findings, are built to simulate urban residential phenomena, such as gentrification (Diappi and Bolchi, 2008; Jackson et al., 2008; O'Sullivan, 2002; Torrens and Nara, 2007) and urban sprawl (Brown et al., 2008; Fernandez et al., 2005; Loibl and Toetzer, 2003),

The advantages of ABM is that it can go beyond some restrictive assumptions of other modeling techniques in accommodating bounded rationality and heterogeneity among agents, out-of-equilibrium dynamics, and interactions, which gives modelers much more freedom in model design. While the importance of these features in general has been extensively discussed (An, 2012; Arthur, 1999; Axtell, 2000; Bonabeau, 2002; Epstein, 1999; Manson et al., 2012; O'Sullivan et al., 2012; Parker et al., 2003), three aspects that are vital for modeling urban phenomena have not been reviewed thoroughly.

The first one is agent heterogeneity. As Irwin (2010) acknowledged, agent heterogeneity, which is defined as “key differences among individual households, firms or other agents, e.g., differences in preferences, wealth, technology or expectations” (page 69), is an important driving force for spatial land-use dynamics. However, there is no common agreement on either how to incorporate agent heterogeneity or how to evaluate the effects of agent heterogeneity on the aggregated urban dynamics and patterns, especially with multiple sources of agent heterogeneity. The second is the extent of land market representation, which influences residential choice and consequent land-use change (Parker et al., 2012b). The degree of representation of land market processes in existing models varies greatly. Yet, progresses on representing land market processes and their effects on spatial and socioeconomic outcomes have not been fully reviewed. The third essential feature is methods to measure the variety of outcomes resulting from agent heterogeneity and land market representation. ABMs provide both aggregated spatial and socioeconomic outcomes and disaggregated outcomes at the agent level, which demand not only traditional spatial metrics but also other methods to analyze the outcomes (Herold et al., 2005; Huang et al., in review; Parker and Meretsky, 2004; Sun et al., in review).

In the light of rapid growth of applications of agent-based urban land-use change models, this chapter reviews recent urban agent-based residential choices models. The purpose of this chapter is twofold. First, it surveys the literature on the simulation of urban residential choice rooted in ABM, with a focus on the progress of the representation of agent heterogeneity, land market processes, and output measurement. Second, this chapter aims to identify and discuss the research gaps underlying these progresses in order to improve model development and authenticity of models.

In order to guarantee comparability among models, four criteria are used to select models: (1) their main objective is to simulate residential choice in the context of urban development, (2) they are based on ABM techniques or microsimulation models (MSM),

(3) they are spatially explicit, and (4) their results are published in peer-reviewed journals, book chapters or conference proceedings.

According to these four criteria, 51 models were reviewed, and three main research domains were identified. The three aspects of models in each research domain are summarized and compared in section 4.2. In section 4.3, three distinctive features brought by ABM into urban modeling, namely, agent heterogeneity, land market representation and measurement of outcomes, are discussed in detail. Specifically, the methods of introducing agent heterogeneity are compared, and gaps in methods evaluating heterogeneity are emphasized. Then, four essential elements of land markets — locational preference, resources constraints, competitive bidding, and endogenous relocation — are compared. Open questions concerning land market representation are also addressed. In section 4.4, we discuss the current methods for and challenges in measuring ABM outcomes. The final section offers a brief summary and discusses general outstanding challenges in this area.

4.2 Modeling urban phenomena with ABMs: Three research domains

Following the continuum defined by Parker et al. (2002), which runs from purely theoretical to intensively empirical models, we identify three research domains across the 51 reviewed models: (i) variations of classical stylized models, which are commonly constructed based on classical theories (e.g., Schelling’s segregation model, Alonso/Von Thünen model); (ii) models simulating different stages of the urbanization process, which combine theories and empirical findings (e.g., urban sprawl, urban shrinkage, urban expansion, and gentrification); and (iii) microsimulation of urban systems integrated with ABM, which are largely driven by empirical data to replicate details of a specific case

study. The detailed review of models within each research domain is discussed below.

4.2.1 Classical models and variations

A series of stylized ABM models have been developed to investigate questions central to the development of urban form: how patterns of residential segregation, land use, and land value emerge. These ABMs often build on paradigmatic theoretical precedents. In the next section, we review two families of such models: Schelling-style residential segregation, and extensions of the monocentric bid-rent model.

4.2.1.1 Schelling's segregation model and its variations

Residential segregation is a common phenomenon in American cities (Clark, 1986; Galster, 1988). It is an outcome of residential choices due to the heterogeneity among resident types, their preferences to be near others of their same type, and locational heterogeneity. Thomas Schelling and James Sakoda independently proposed similar models to explain residential segregation in 1970 (Sakoda, 1971; Schelling, 1971). In these models, space is represented by a checkerboard. Black or white households tend to migrate to a place where local residential familiarity in the neighborhood is acceptable when dissatisfaction in the current neighborhood increases. Households' attitudes toward a household of another color can be attractive, neutral or avoidant. This classical stylized model is designed to be intentionally primitive. The number of each color of households is constant and equal. Their migration decisions are based upon evaluating the residential dissonance measured by the number of other type households within a first order of Queen's neighborhood (i.e., nearest 8 cells surrounding a host cell).

These models demonstrate that segregation patterns can emerge from individual migration decisions, even with a modest preference for similar neighbors. In the last few

decades after the model was proposed, improvements in computing capacity and technology have enabled researchers to explore and extend the basic results in various ways. In fact, the effects on segregation have been evaluated by changing almost all the input parameters or different combinations of input parameters. Table 4-1 lists some representative extensions of the original model based on ABMs. The main extensions include (but are not limited to):

- The division of space is replaced from a traditional grid to a Voronoi partition (Benenson, 1999; Benenson et al., 2002; Omer, 2005) or a vector layer (Crooks, 2010).
- The representation of space varies from homogeneous and featureless to heterogeneous based on empirical conditions (Yin, 2009).
- The traditional two types of residents (i.e. black and white) are extended to three groups derived from an empirical survey in Los Angeles (Clark and Fossett, 2008), four groups in London (Crooks, 2010), and two-level hierarchical groups (2 top groups and 2 sub groups for each top group) in Tel Aviv (Omer, 2005). Additionally, Ellis et al. (2011) introduced another group of households, mixed-race households, in their model. Accordingly, residents' preferences of a given group for other groups are not equal and can vary from group to group.
- In addition to the original 8 neighbors, e.g., Queen's neighborhood, various shapes and sizes of neighborhoods are examined (Fossett and Dietrich, 2009; Laurie and Jaggi, 2003). A hierarchical neighborhood (O'Sullivan et al., 2003), neighborhoods considering barrier effect of natural elements (i.e. river) (Crooks, 2010) and streets (Benenson, 1999), and block neighborhood defined by census (i.e. block) (Yin, 2009) are also implemented.
- The migration strategies are distinguished between "satisficer" and "maximizer" (Benenson and Hatna, 2011). The former is willing to accept any potential property with higher utility or satisfying level, while the latter only move to the location

providing the highest utility or satisfying level.

Table 4-1 Comparison of Schelling's segregation model and its variations

Label	Space	Groups of households	Number of households within group	Neighborhood	Migration strategies	Extra factors
(Laurie and Jaggi, 2003)	grid	2	equal	8 (3*3 Queen)	satisficer	
(O'Sullivan et al., 2003)	grid	2	equal	distance (1-5)	satisficer	
(Fossett and Waren, 2005)	grid	2	equal	2 levels of neighbors	satisficer	
(Fossett and Dietrich, 2009)	grid	2	uneven	48 (7*7)	maximizer	
(Clark and Fossett, 2008)	grid	2	uneven	varying types	maximizer	
(Wasserman and Yohe, 2001)	grid	3	uneven	40 neighbors	maximizer	income, housing quality
(Crooks, 2010)	grid	2	equal	exponent decayed	satisficer	location, public good
(Benenson and Hatna, 2011; Hatna and Benenson, 2012)	vector	2 or 4	uneven (empirical)	buffering and constrained by natural barrier	satisficer	natural barrier
(Omer, 2005)	grid	2	uneven	5*5	satisficer	
(Torrens, 2007)	vector	4	equal	8 (3 * 3 Queen)	satisficer	
(Benenson et al., 2002)	grid	3	uneven	Regional and local	satisficer	wealth, inertia, property type
(Benenson, 1999)	Voronoi partition	continuous	uneven (empirical)	distance and Street barrier	satisficer	housing style
(Yin, 2009)	grid or vector	continuous	empirical	Queen's neighborhood or buffering and street barrier	satisficer	income, housing value, cultural code
(Bruch and Mare, 2006, 2009; Xie and Zhou, 2012)	grid and empirical	2	uneven	block boundary	satisficer	housing sale price
(Crooks, 2006)	grid	2	equal	5*5	satisficer	
(Ellis et al., 2011)	grid	6	uneven	Queen's second-order contiguity rule	satisficer	

- Besides ethnic composition, more driving forces for segregation, such as income and house quality (Clark and Fossett, 2008), attractiveness of public goods (Wasserman and Yohe, 2001), cultural differences (Benenson, 1999), property type and agent's inertia (Torrens, 2007), are simulated to replicate the real conditions.

4.2.1.2 Von Thünen/Alonso's model and its variations

In addition to residential segregation, researchers have developed models to explain urban spatial structure and the location of households and firms. This stream of studies is rooted in location theory. During the 19th century, J. von Thünen developed the conceptual basis for economic bid-rent theory to account for the spatial distribution of agricultural activities around the central business district (CBD) (Von Thünen, 1966). In the von Thünen model, decision-makers bid on the land around CBD depending on their transport costs, production costs and market prices of agricultural goods. The land is allocated to the highest bidder. Then concentric rings of different crops are formed around the market center due to the differences in the costs and prices of agricultural goods. The von Thünen model was extended and applied to the urban context by Alonso (1964), Muth (1969) and Mills (1972). In the monocentric city model, a CBD is located in the center of the city, which serves as a proxy for access to cultural and business opportunities. Residents make bidding choices that maximize their utilities under the tradeoff between commuting and housing costs. Land is allocated to the resident who provides the highest bid. Spatial equilibrium culminates with a declining trend of population density, land value, and housing price from the CBD (Anas et al., 1998; Parker and Filatova, 2008). Analytical extensions of the original Alonso model have been developed by incorporating developers' decision on development density (Mills, 1972; Muth, 1969), open-space amenities and spatial externalities (Caruso et al., 2007; Cavailhès et al., 2004; Irwin and Bockstael, 2002; Wu and Plantinga, 2003). This field

has developed further to create polycentric extension on the original monocentric city model (see Fujita and Ogawa, 1982; Fujita and Thisse, 2002; Harris, 1985; Munroe, 2007; Ogawa and Fujita, 1980 for review).

In addition to spatial analytical models, ABMs are used to extend the traditional monocentric city model by allowing interactions of heterogeneous agents and market disequilibrium in the model. Table 4-2 summarizes some representative features implemented in existing models:

Table 4-2 Representative features of Von Thünen/Alonso's model and its variations

References	Price formation	Bidding or negotiation	Spatial externalities	Agent heterogeneity	Monocentric & leapfrog	Others
(Crooks, 2006)	yes	yes	n/a	yes	n/a	Interactions with firms, dynamic attributes evolves with time
(Filatova et al., 2009a; Filatova et al., 2011a)	yes	yes	yes	yes	both	Heterogeneous risk attitudes
(Gilbert et al., 2009)	yes	no	no	yes	no	Realtor, time dynamics
(Magliocca et al., 2011)	yes	yes	no	yes	both	Building heterogeneity, developer
(Chen et al., 2011)	yes	yes	no	yes	both	Optimal timing of development
(Ettema, 2011)	yes	yes	no	yes	no	Relocation, perceptions of housing market probabilities

The most common feature among the six models listed in Table 4-2 is that they have price formation functions. This implies that each local transaction price emerges from interactions between buyers and sellers, rather than a fixed land rent being imposed on the model exogenously.

When simulating endogenous transaction prices, the majority of models have an endogenous willingness to pay (WTP) function of buyers, which depends on both spatial and agent-level factors. In the bid-rent model developed by Crooks (2006), the bidding price is formed based on residents' income and preference heterogeneity as well as travel cost and required space. In ALMA (an Agent-based Land Market) model (Filatova et al., 2009a), buyers' WTP is based on their utilities (calculated by preferences for open-space amenity and proximity to the CBD), transport cost, budgets and non-housing costs. In the model proposed by Gilbert et al. (2009), other than the assumption of utility maximization, they assume buyers will purchase the most expensive property they can afford assuming that housing price reflects the house quality. The transaction prices are affected by buyers' heterogeneous incomes and preferences. In the CHALMS (Coupled Housing And Land MarketS) model (Magliocca et al., 2011), households' bidding prices depend on characteristics of the house and on lot size, travel cost, households' preferences for housing type and developers' asking price. In the model developed by Chen and his colleagues (2011), the bidding price is not only dependent on the number of competitors but also on the income distribution, which evolves over time. Another agent-based housing market model proposed by Ettema (2011) adopted an alternative strategy in price formation. Rather than simulating explicit WTPs or WTAs (willingness to accept), a buyer or a seller formulates a specific probability of buying or selling the property at a given listed price. These perceptions of housing market probabilities are updated over time based on the negotiation in the market, and affect resulting housing prices.

These price formation functions allow for inclusion of a certain level of spatial and agent heterogeneity, such as differences in locations, housing types, preferences, incomes, and risk attitudes. Thus, all the models in Table 4-2 have the feature of agent

heterogeneity.

Due to spatial and agent heterogeneity, models are able to simulate expectation formations of future prices. For example, Chen et al. (2011) simulated landowners' expected value of land based on current agricultural rent and future return of selling the land. And in CHALMS both farmers and developers employ various prediction strategies to form their expectations of future land and housing prices respectively (Magliocca et al., 2011). In Ettema's model (2011), the probabilities of selling or buying a house are determined by expected return for a given house within a given period and updated over time by a Bayesian learning procedure based on past transactions.

Additionally, spatial and agent heterogeneity enables models to simulate other complex behaviors of buyers and processes of market, for example:

- Bidding prices are further adjusted by different market conditions. In ALMA, bidding prices are adjusted by the relative market power of buyers and sellers (i.e. excess of demand or supply) (Filatova et al., 2009a). In the model developed by Chen et al. (2011), the bidding prices are influenced by the number of participants in the competition. In CHALMS, bidding prices of consumers are also impacted by a housing market competition factor which reflects the competition each consumer faces from other consumers on a number of available houses (Magliocca et al., 2011).
- Heterogeneous risk attitudes can affect the patterns of land development and land rent, as indicated by the ALMA model (Filatova et al., 2011a; Filatova et al., 2009b).
- The effects of economic incentives, e.g. tax, on protecting coastal environment was demonstrated in ALMA (Filatova et al., 2011b).

In addition to the classical result of declining house price from the CBD, three models are able to simulate leapfrog development in the urban-rural fringe, even though they have adopted different theories to explain this pattern. In ALMA (Filatova et al., 2009a), the tradeoff between open-space amenity (i.e. spatial

externality) and proximity to the CBD is the main driver for the fragmented development in exurban area. In the CHALMS (Magliocca et al., 2011), the sprawl and leapfrog development is simulated by various sources of spatial and agent heterogeneity (including agricultural productivity of parcels, house size, lot size, households' incomes and preferences for housing types, and farmers' and developers' expectations of future prices) and market interaction between farmers and developers, and between developers and households in the land and housing market. In the last model developed by Chen et al. (2011), the emergence of leapfrog development arises from spatial heterogeneity in competition and agent heterogeneity in income that give priorities for richer households in choosing the locations with less competition and less constrained by commuting cost. In the real world it is likely to be a combination of these factors behind the observed leapfrog development pattern.

Some models extend traditional initial landscape configuration by incorporating empirical spatial elements. In ALMA-C, a coastal area with higher amenity and coastal hazard levels is simulated based on the empirical finding in coastal areas of Netherlands (Filatova et al., 2011a; Filatova et al., 2011b). In CHALMS, the land surrounding the CBD is divided into fifty farms and their attributes are derived from census data in suburban counties in the Mid-Atlantic region. Due to the empirical configuration of landscape, the final spatial pattern of development is more distinguished from the pattern of classical monocentric model (Magliocca et al., 2011). The model developed by Crooks (2006) moves away the restrictive assumption of centralized employment by introducing heterogeneous firms across the landscape. Location of residents and firms are determined by the competition between firms and residents and feedbacks between agents and the environment.

4.2.2 Different stages of urbanization process

The domain of urbanization process models embraces semi-empirical ABMs, which were developed to study empirical facts. Agents' behavior in these ABMs is often rooted in disciplinary theories; empirical data is employed to partially parameterize

agents and/or the landscape. Due to the differences in their local physical and socioeconomic environment, cities experience specific urbanization processes and face distinctive challenges brought in these given contexts. Models are developed to capture the residential choices in different processes of urbanization. These models are usually based partially on theoretical findings and partially on empirical data from a specific urbanization processes. For instance, Ligmann-Zielinska (2009) developed an ABM to evaluate the impacts of developers' risk attitudes on the fragmentation of development in an hypothetic urban area. Heckbert and Smajgl (2005) and Li and Liu (2007) developed regional projects and models by incorporating various empirical factors to simulate residential choices in Austrian cities and a fast growing city in China respectively. Thus, urban residential choice models regarding the simulation of different stages of urbanization process vary greatly. Yet, there are some common characteristics, which can be summarized as follows:

First, the manifestation of urbanization is different between developing countries and developed countries. Both the driving forces of urbanization and the patterns of land-use change can substantially vary, for example:

- In developing countries, the growth of informal settlements, which are established without planning regulations and basic facilities, is modeled in Dar es Salam, Tanzania (Augustijn-Beckers et al., 2011). The peripherisation, defined as “formation of low-income residential areas in the peripheral ring of the city and a perpetuation of a dynamic core-periphery spatial pattern” (p. 571), is simulated in Latin American cities (Barros, 2012). The rapid urbanization of a densely rural population in a newly developed region, known as Desakota, is simulated in China (Xie et al., 2007).
- In developed countries, different phenomena are under inspection. For instance, models are proposed to test theoretical hypotheses of gentrification theory (Diappi and Bolchi, 2008) and in empirical contexts (e.g., in east London, (O'Sullivan, 2002), Boston (Jackson et al., 2008) and Salt Lake City (Torrens, 2007)).
- The understanding of another urbanization phenomena, urban sprawl (or suburbanization), is also facilitated by ABMs. Urban sprawl in Southeastern

Michigan is simulated by the SOME (Sluce's Original Model for Exploration) and the DEED (Dynamic Ecological Exurban Development) models developed by Brown and his colleagues (Brown et al., 2004a; Brown et al., 2008; Fernandez et al., 2005; Rand and Brown, 2002; Robinson and Brown, 2009; Zellner et al., 2010). Other applications of urban sprawl models can be found in Vienna Region (Loibl et al., 2007; Loibl and Toetzer, 2003), northwest of Lyons, Boulder County (Yin and Muller, 2007) and Brussels periurban area (Caruso et al., 2005). The feedbacks between segregation and suburbanization are also analyzed by a stylized ABM (Jayaprakash et al., 2009).

- Urban shrinkage, which is characterized by a large amount of residential vacancies resulting from an oversupply of dwellings, is also a hot topic among modelers. For instance, residential mobility in a shrinking city of Leipzig in Eastern Germany is simulated by an ABM called RESMOBcity (Haase et al., 2010).

Second, the majority of models in this category are policy oriented. In other words, policy and planning strategies and their influence on urban physical morphology, socioeconomic outcomes and environmental consequence are evaluated via what-if scenarios in most empirical applications. For instance, land-use strategies encouraging compact development are examined by an ABM that has the ability to measure the compactness of the city from the perspective of transport efficiency, energy consumption and residents' welfare (Kii and Doi, 2005). The influence of residential, commercial and industrial development on the forest ecosystem under different management strategies is evaluated in Texas, USA (Monticino et al., 2007). Sustainable development strategies are embedded in an ABM to regulate agents' behavior in a rapidly expanding city in China (Li and Liu, 2008). Beliefs and preferences on spatial objects from multiple actors are simulated in a hypothetical planning scenario in the Netherlands to support decision-making of spatial planners (Ligtenberg et al., 2001; Ligtenberg et al., 2004). And an urban regeneration policy that intends to encourage social mixing in the UK is simulated in an agent-based housing choice model to evaluate its effects on vitality of housing market and

availability of jobs (Jordan et al., 2011, 2012).

Third, to cope with the data limitations and complexity in individual urbanization processes, an ABM is commonly integrated with other modeling techniques. For example, a hybrid model combining ABM, logistic regression, and neighborhood effects is used to simulate the impacts of land-use change on agricultural soil, noise pollution and quality of life in the Municipality of Koper, Slovenia (Robinson et al., 2012). Another model integrating multi-objective land use allocation and ABM is applied to evaluate the influences of suburbia and exurbia under different planning situations in a community in Washington State, USA (Ligmann-Zielinska and Jankowski, 2007, 2010). The urban growth for the Phoenix metropolitan region of the United States is predicted by a hybrid model of ABM and spatial regression under three scenarios (Tian et al., 2011). And the new version of SLUCEII-ABM model integrates individual's behaviors in land markets and land management by using an ABM and an ecosystem model BIOME-BGC to evaluate the dynamic land-cover and land-use change and subsequent influence on carbon storage and flux (Parker et al., 2012a; Robinson et al., in press).

4.2.3 ABM and microsimulation modeling

According to the International Microsimulation Association (2012), microsimulation (MSM) is defined as “a modeling technique that operates at the level of individual units such as persons, households, vehicles or firms”. Each individual contains various unique attributes and follows a set of behavioral rules. MSM was introduced in 1950s by Orcutt (1957) in his attempt to develop an approach that is different from traditional aggregated models to model the diversity of U.S. economic system (Clarke and Holm, 1987). This technique has been increasingly applied in simulations of tax-benefit, social/fiscal policy, demographic dynamic, health, traffic flows, firms and enterprises (Birkin and Wu, 2012; Zaidi and Rake, 2001).

MSM is closely parallel to two other individual-level modeling approaches: Individual-based Modeling in ecology (see Bousquet and Le Page, 2004; Grimm and

Railsback, 2005 for review) and ABM. Both MSMs and ABMs simulate individual's decision-making process based on agents' heterogeneous attributes and their interactions with the environment and other individuals. MSM is more inductive approach and relies heavily on methods that infer from aggregated patterns to individual agents, such as regression analysis, probabilistic modeling (Mahdavi et al., 2007). In contrast, ABMs are typically used to combine inductive and deductive approaches (Axelrod, 1997; Nolan et al., 2009) and simulate aggregated pattern as an emergent cumulative effect of individual behaviors. In addition, the specialty of MSMs is to predict the impacts of policy changes on a population of agents based primarily on historic data, which is used for fitting the statistical model. On the contrary, ABMs are more suitable when new dynamics, critical transitions and switching to different regimes (economic crisis, housing bubble) is expected. This is due to the fact that individual agents' behaviors can be driven by adaption and evolutionary learning rooted in artificial intelligence, which leads to the emergence of new strategies and changes in preferences and risk attitudes. However, Brikin and Wu (2012) acknowledge, the boundary between MSMs and empirical spatial ABMs are likely to fade away over time, and the relationship between the two approaches is better described as complementary.

In the light of the complementary relationship and sometimes vanishing boundary between MSM and ABM, a series of empirical models integrating MSM with ABM have been developed to project urban system dynamics. Table 4-3 lists 8 models which falls into this category, and compares their differences. They are UrbanSim in USA (Waddell, 2002; Waddell et al., 2003; Waddell et al., 2008), MALUT (Multi-Agent Land-Use and Transport) in Japan (Kii and Doi, 2005), ILUTE (Integrated Land Use, Transportation, Environment) in Canada (Miller et al., 2008), ILUMASS (Integrated Land-Use Modelling and Transportation System Simulation) in Germany (Wagner and Wegener, 2007), PUMA (Predicting Urbanisation with Multi-Agents) in Netherlands (Ettema et al., 2007), HI-LIFE (Household Interactions through LIFE cycle stages) in England (Fontaine and Rounsevell, 2009), Agent iCity in Canada (Jjumba and Dragičević, 2011), MoSeS (Modelling and Simulation for e-Social

Science) in England (Wu and Birkin, 2012; Wu et al., 2008). By reviewing these models, some common features can be identified.

First, most models (6 out of 8) have multiple types of agents. The model will simulate the moving and residential choice of households, the location and real estate type choice of developer, location choice of firm and business, and policy and planning proposed by government and planning authorities (see Table 4-3).

Second, life-cycle events and daily activities (e.g., travel routines to work or shopping) play an important role in influencing residential choice in these models. A large population of heterogeneous individuals will make a residential choice according to their socio-demographic attributes, such as age, marital status, child birth, job location, and shopping patterns. ABM is fused into MSM contributing with ability to simulate the social behavior of individuals, such as preferences, risk attitudes, and plans (Birkin and Wu, 2012).

Third, another feature of these models is that they are highly related to policy and planning analysis. Thus, the population dynamics, travel patterns, and consequences of urban land-use change are simulated based upon various what-if scenarios. According to Table 4-3, all of these models have evaluated policy-related scenarios, and more than half of them incorporate traffic patterns (5 out of 8). In addition, environmental consequences of energy consumption (Chingcuanco and Miller, 2012; Kii and Doi, 2005), air pollution (e.g., greenhouse gas emission, air quality, population exposure) and noise (Hatzopoulou et al., 2011; Wagner and Wegener, 2007) are assessed.

Table 4-3 Microsimulation models containing urban residential location and their characteristics

Citations	Model name	Study area	Agent type	Transport pattern	Policy scenarios	Environmental effects
(Ettema et al., 2007)	PUMA	Northern part of the Dutch Randstad, Netherlands	Farmer, Authority, Investor, Developer, Household, Firm	Yes	Yes	No
(Fontaine and Rounsevell, 2009)	HI-LIFE	East Anglia, UK	Households	No	Yes	No
(Jumba and Dragičević, 2011)	Agent iCity	City of Chilliwack, Canada	Planner, Developer, Household, Retailers, Industrialists	No	Yes	No
(Kii and Doi, 2005)	MALUT	Takamatsu city, Japan	Household, Firms	Yes	Yes	Yes, energy consumption
(Miller et al., 2008; Salvini and Miller, 2005)	ILUTE	Greater Toronto Area, Canada	Developer, Household, Firm	Yes	Yes	Yes, energy consumption, greenhouse gas emission, and air quality
(Waddell, 2002; Waddell et al., 2003; Waddell et al., 2008)	UrbanSim	Eugene-Springfield, Oregon, USA	Household, Business, Developer, Government	Yes	Yes	No
(Wagner and Wegener, 2007)	ILUMASS	Metropolitan area of Dortmund, Germany	Household, Business, Developer	Yes	Yes	Yes, air quality, traffic noise
(Wu and Birkin, 2012)	MoSeS	Leeds, UK	Household	No	Yes	No

Fourth, all of these models are developed and applied in cities in developed countries. The reason, on the one hand, is due to the prominent impact of urban development in developed countries. Considerable attention is drawn to meet the challenges of socioeconomic and environmental consequences of urbanization. On the other hand, MSMs require abundant data consisting of census tables, housing surveys, remotely sensed images, and traffic records. These data are rarely recorded or available at the extent required by MSMs in developing countries.

Last, all of these models belong to long-term ongoing projects. For instance, the ILUTE model developed by a group of researchers in the University of Toronto and lead by Dr. Eric Miller was firstly presented in 1998 (Miller et al., 2008; Salvini and Miller, 2005). After its initial framework, continuing efforts are made to synthesize the population data (Pritchard and Miller, 2012), improve the performance and the authenticity of the model (e.g., a new module simulating disequilibrium dwelling space under different market conditions (Farooq and Miller, 2012)), and validate the results (Miller et al., 2011). Other projects follow similar long-term improving development patterns.

All the 51 models, grouped by research domains, are listed in Table 4-4. It is clear that some models cover more than one domain. From the third column, which represents the data used in the model, it is also evident that some long-term projects tend to develop from a purely theoretical stylized model to a more realistic model driven by empirical data (i.e. the space is still highly abstract but parameterization is driven by empirical data) and then to a fully empirical model. Table 4-4 also compares additional features among these models, as explained in the next section.

Table 4-4 Market representation and agent heterogeneity in existing agent-based urban land-use models

Model Name / Main Developers	Domain	Data	Agents	Resources Constraints	Competitive Bidding	Endogenous Relocation	Measures of performance	Sources of agent heterogeneity	Effect of agent heterogeneity
OBEUS/Benenson ^[1]	Se	Both	R	yes	no	yes	SD+ SI	3	yes
MASUS ^[2]	Se	Empirical	H	yes	no	n/a	SD+ SI	3	yes
Simseg ^[3]	Se	Both	H	yes	yes	yes	SD+ SI	3	no
O'Sullivan ^[4]	Se	Artificial	R	no	no	yes	SD+ SI	1	no
Laurie and Jaggi ^[5]	Se	Artificial	R	no	no	yes	SD+SI	2	no
Yin ^[6]	Se	Empirical	R	yes	no	yes	SD+ SI	2	no
Wasserman and Yohe ^[7]	Se	Artificial	R	no	no	yes	SD+ SI+AM	2	no
Xie ^[8]	Se	Semi-E	R	no	no	yes	SI	1	yes
Bruch ^[9]	Se	Artificial	R	no	no	yes	SI	1	yes
Benenson ^[10]	Se	Artificial	R	no	no	yes	SD+SI	1	no
Gilbert ^[11]	Se	Semi-E	R+A	yes	no	yes	SD+SM+AM	1	no
Ellis ^[12]	Se	Artificial	R	no	no	yes	SI	1	no
Crooks ^[13]	Se/Mo	Artificial	R+B	n/a	n/a	n/a	SD+ SI	1	no
Jayaprakash ^[14]	Se+Ur	Artificial	R	yes	no	yes	SD+ SI	3	no
Jordan ^[15]	Se+Ur	Empirical	R	yes	no	yes	SD+LM	>3	no
ALMA (ALMA-C) ^[16]	Mo	Artificial	R+F	yes	yes	no	SD+LM+SM	1	yes
CHALMS ^[17]	Mo	Empirical	H+D+F	yes	yes	no	LM+SM	3	no
Chen ^[18]	Mo	Semi-E	H+F+A	yes	yes	no	SD+AM+SM	2	yes
SOME ^[19]	Ur	Both	R	no	no	no	SD+LM+AM	1	yes

Model Name / Main Developers	Domain	Data	Agents	Resources Constraints	Competitive Bidding	Endogenous Relocation	Measures of performance	Sources of agent heterogeneity	Effect of agent heterogeneity
SOME+DEED ^[20]	Ur	Both	R+D+F+G	no	no	no	EM	1	no
Caruso ^[21]	Ur	Both	R+F	yes	yes	yes	SD+LM+SM	0	no
Diappi ^[22]	Ur	Artificial	R+D+T+L	yes	n/a	yes	SD	2	no
Ligmann-Zielinska ^[23]	Ur	Artificial	D	no	yes	no	SD+LM	1	yes
Jackson ^[24]	Ur	Empirical	R	yes	n/a	yes	SD	4	no
Torrens ^[25]	Ur	Artificial	R	yes	no	yes	SD	>3	no
Xie ^[26]	Ur	Empirical	D+B	no	no	no	SD+SM	1	no
O'Sullivan ^[27]	Ur	Empirical	R+T+L	yes	no	yes	n/a	2	no
STAU-Wien ^[28]	Ur	Empirical	H+B	no	no	no	SD	>3	no
ABLOoM ^[29]	Ur	Artificial	H+B	yes	no	no	SD	>3	no
Sasaki ^[30]	Ur	Artificial	F	yes	no	yes	SD+LM	2	no
Li ^[31]	Ur	Empirical	H+D+G	yes	no	yes	SD	3	no
Tao and Li ^[32]	Ur	Empirical	H	yes	n/a	yes	SD+SM	1	no
Yin and Muller ^[33]	Ur	Empirical	H	no	no	no	SD+LM	1	no
Augustijn-Beckers ^[34]	Ur	Empirical	R+T	yes	no	no	SD+LM	3	no
RESMOBcity ^[35]	Ur	Empirical	H	no	no	no	SD+AM	>3	no
Barros ^[36]	Ur	Empirical	R	yes	yes	yes	SD+ SI	1	no
Tian ^[37]	Ur	Empirical	G+D+H+E	no	no	no	SD+LM	>3	no
SLUCEII-ABM ^[38]	Ur+Mo	Empirical	R+F+D+A	yes	yes	yes	SD+LM+EM	>3	no
MOLA + ABM ^[39]	Ur+PI	Empirical	D	no	no	no	SD+LM	1	no
Robinson ^[40]	Ur+PI	Empirical	R+D+F	no	no	no	SD+EM	>3	no

Model Name / Main Developers	Domain	Data	Agents	Resources Constraints	Competitive Bidding	Endogenous Relocation	Measures of performance	Sources of agent heterogeneity	Effect of agent heterogeneity
Monticino ^[41]	Ur+PI	Empirical	F+D+G+R	yes	no	no	SM	1	no
AusUrbia ^[42]	Ur+PI	Empirical	F+R+D	yes	yes	yes	SD+SM+AM	>3	no
Ligtenberg ^[43]	Ur+PI	Empirical	H+P	no	no	no	SD+LM	2	no
Jjumba ^[44]	Ur+PI	Empirical	P+D+H+B	yes	no	yes	SD+LM	2	no
PUMA ^[45]	MS	Empirical	B+H+F+G+D	yes	n/a	n/a	SD	>3	no
ILUMASS ^[46]	MS	Empirical	B+D	yes	n/a	yes	SD	>3	no
UrbanSim ^[47]	MS	Empirical	G+H+B+D	yes	n/a	yes	n/a	>3	no
ILUTE ^[48]	MS	Empirical	D+H+B	yes	yes	yes	n/a	>3	no
MALUT ^[49]	MS	Empirical	H+B	yes	yes	yes	SD+EM	3	no
MoSeS ^[50]	MS	Empirical	R+T	no	no	no	SD+LM	>3	yes
HI-LIFE ^[51]	MS	Empirical	H	yes	no	yes	SD+AM	>3	no

Notes: Se: segregation; Mo: monocentric city and its variation; Ur: urbanization stage; PI: Planning; MS: microsimulation

Semi-E: semi-empirical (only the parameters are derived from empirical data, the space is artificial)

R: residents; F: Farmer (landowner); D: developers; G: government; H: households; T: Tenant; L: landlord; B: business (firms); P: planner; E: environmentalist; A: Auctioneer (broker, or real estate agent)

SD: spatial distribution of land use; LM: landscape metrics; SM: socioeconomic metrics; AM: agent level metrics; SI: segregation index; EM: environmental measures

^[1](Benenson, 1998; Benenson, 1999; Benenson et al., 2005; Benenson et al., 2002; Omer, 2005); ^[2](Feitosa et al., 2011); ^[3](Fossett, 2006a, b; Fossett and Dietrich, 2009; Fossett and Waren, 2005); ^[4](O'Sullivan et al., 2003); ^[5](Laurie and Jaggi, 2003); ^[6](Yin, 2009); ^[7](Wasserman and Yohe, 2001); ^[8](Xie and Zhou, 2012); ^[9](Bruch and Mare, 2006, 2009); ^[10](Benenson and Hatna, 2011; Hatna and Benenson, 2012); ^[11](Gilbert et al., 2009); ^[12](Ellis et al., 2011); ^[13](Crooks, 2006; Crooks, 2008); ^[14](Jayaprakash et al., 2009); ^[15](Jordan et al., 2012); ^[16](Filatova et al., 2009a; Parker and Filatova, 2008); ^[17](Magliocca et al., 2011); ^[18](Chen et al., 2011); ^[19](Brown et al., 2005b; Brown et al., 2004a; Brown and Robinson, 2006; Zellner et al., 2010); ^[20](Brown et al., 2008);

^[21] (Caruso et al., 2007; Caruso et al., 2009; Caruso et al., 2005); ^[22] (Diappi and Bolchi, 2008); ^[23] (Ligmann-Zielinska and Jankowski, 2010); ^[24] (Jackson et al., 2008); ^[25] (Torrens, 2007); ^[26] (Xie et al., 2007); ^[27] (O'Sullivan, 2002); ^[28] (Loibl et al., 2007; Loibl and Toetzer, 2003); ^[29] (Otter et al., 2001); ^[30] (Sasaki and Box, 2003); ^[31] (Li and Liu, 2007); ^[32] (Tao et al., 2009); ^[33] (Yin and Muller, 2007); ^[34] (Augustijn-Beckers et al., 2011); ^[35] (Haase et al., 2010); ^[36] (Barros, 2012); ^[37] (Tian et al., 2011); ^[38] (Parker et al., 2012a; Robinson et al., 2010); ^[39] (Ligmann-Zielinska, 2009; Ligmann-Zielinska and Sun, 2010); ^[40] (Robinson et al., 2012); ^[41] (Monticino et al., 2007); ^[42] (Heckbert and Smajgl, 2005); ^[43] (Ligtenberg et al., 2004); ^[44] (Jjumba and Dragičević, 2011); ^[45] (Ettema et al., 2007); ^[46] (Wagner and Wegener, 2007); ^[47] (Waddell, 2002; Waddell et al., 2003; Waddell et al., 2008); ^[48] (Miller et al., 2008; Salvini and Miller, 2005); ^[49] (Kii and Doi, 2005); ^[50] (Wu and Birkin, 2012; Wu et al., 2008); ^[51] (Fontaine and Rounsevell, 2009).

4.3. Urban residential choice model based on ABM

One of the essential differences between an ABM and previous models (e.g., system dynamics, cellular automata) is its ability to simulate emergent pattern from decision-making processes and behaviors of individual intelligent agents. This ability grants modelers more freedom to explicitly model causal factors, agents' behaviors, and to represent model output. As modelers are free to decide upon these features, technically there are no binding conditions on what can and what cannot be put into an ABM. This flexibility results in great variety of ABMs. This review of ABMs further focuses on the three features: agent heterogeneity, representation of market process, and measurement of output.

4.3.1 Agent heterogeneity

Agent heterogeneity is one of the main reasons that ABM is attractive to researchers in simulating residential choice in an urban context (Huang et al., in review). The limitations and restrictions of a single representative agent and the requirement for static equilibrium conditions faced by traditional economic models can be relaxed to include agent heterogeneity (Arthur, 1999, 2005; Axtell, 2000, 2003; Epstein, 1999; Farmer and Foley, 2009; Hommes, 2005; Tesfatsion, 2006). While some analytical urban models incorporate agents' heterogeneity, they do it only within a 1D landscape, which can be heterogeneous in maximum two attributes, because the difficulty in finding an analytical solution increases prominently as incorporating one source of agent heterogeneity (Anas, 1990; Epple and Platt, 1998; Irwin, 2010). Moreover, a greater variety of emergent landscape patterns and LUCC phenomena can be simulated from the bottom up, for example, urban sprawl, urban gentrification, and residential segregation. (Benenson and

Torrens, 2004a; Chen et al., 2011; Macy and Willer, 2002; Wu and Plantinga, 2003).

4.3.1.1 Ways to model agents' heterogeneity

From a broad perspective, heterogeneity among agents in an ABM can be introduced through multiple types of agents. The interactions between different types of agents may also lead to different model outputs. In this review, however, we define agent heterogeneity in a more narrow way. Specifically, agent heterogeneity refers to differences in attributes and decision-making rules among individuals within the same agent type. The differences could be either internal (e.g., demographic and household characteristics, personal experiences, expectations, and risk attitudes) or external (e.g., social networks, accessibility to information, and policies) (Irwin, 2010; Valbuena et al., 2008).

The method to incorporate agent heterogeneity into an urban ABM depends on the objective of the study and data availability in an empirical case study (Smajgl et al., 2011). Based on the division between categorization and variation proposed by Brown and Robinson (2006), approaches to introduce agent heterogeneity are divided and categorized in a matrix through the representation of attributes and decision-making rules (see Table 4-5).

Table 4-5 Matrix classification of agent heterogeneity

		Attributes	
		Constant	Variable
Decision-making rules	Constant	I	III
	Variable	II	IV

- I. During an entire model run the attributes and decision-making rules of agents remain constant. Agents are usually identical within the same agent type. Typical examples can be found in the variations of the Schelling's segregation models. In most cases, agents maintain their attributes (i.e. threshold to move) and decision-making rule (i.e. tolerance of neighborhood composition) throughout (Benenson and Torrens, 2004b; Schelling, 1971). Examples can be also found in various empirical models (Diappi and Bolchi, 2008; Kii and Doi, 2005; Tian et al., 2011; Torrens and Nara, 2007).
- II. The second approach is to divide the agents into different groups within an agent type. In this category, agents' attributes are still invariant during an entire model run, but their decision-making rules are differentiated. For example, in the segregation model adopted by Jayaprakash et al. (2009), black residents are indifferent to the composition of residents in the neighborhood, while the white residents are averse to living in a black neighborhood. Another example can be found in the research conducted by Fernandez et al. (2005). They implemented cluster analysis to classify the exurban households into different groups according to their socioeconomic and demographic characteristics. These groups have different preferences (i.e. weights) for residential choices (see also Brown and Robinson, 2006).
- III. In contrast to the former two categories, agents' attributes are no longer invariant in the third and fourth category of ABMs. Their attributes can change with the evolution of time and interaction with other agents and environment. Agents in integrated models with MSMs usually belong to these two categories as life-cycle events, such as marriage, birth of child, divorce, will greatly impact households' decision on the location and preference for a house (e.g., house type, number of rooms, and number of bathrooms). In the third category, agents follow a constant

decision-making function even if some input components are temporally dynamic (e.g., age, number of persons, total income). For example, Barros et al. (2003; 2012) simulated peripherisation in Latin America. In their model, the decision-making rule (i.e., the property is acquired by an agent who is more economic powerful than other bidders) is constant while their attributes, individual income, can vary over time.

- IV. Both the agents' attributes and their decision-making rules vary in the fourth category. In this category, some of agents' attributes will change over time, and when they reach certain conditions, agents will adapt another decision-making rule. For instance, an empirical ABM-MSM is used to simulate the spatial location of student populations in Leeds (Wu and Birkin, 2012; Wu et al., 2008). Four types of students (i.e. first year undergraduate, second-third year undergraduate, master students and Ph.D. students) and their difference in housing priorities are identified by census data and household surveys. More specifically, first year undergraduates tend to stay in university accommodations, and second-third undergraduate would like to choose private rented accommodation. Each agent will experience an aging process and change their rules accordingly.

4.3.1.2 Evaluating the effect of agent heterogeneity

Currently, the most common method of evaluating the effect of agent heterogeneity on the output of ABMs is to compare the results between a baseline scenario with homogeneous agents or agents with random attributes and a scenario with heterogeneous agents (e.g., Brown and Robinson, 2006). The comparison usually supports the importance of agent heterogeneity and demonstrates biases when agent heterogeneity is omitted. For example, Filatova et al (2011a) find qualitatively different results in spatial

and economic metrics in hazard-prone areas (leading to very different policies to be applied) between households with heterogeneous risk perceptions based on the empirical survey distribution and homogeneous agents with risk perception equal to the average of the population.

In addition to that simple comparison, the effect of agent heterogeneity has been further evaluated by varying the distributions of agents' attributes. Using an exurban development model, SOME, Brown and his colleagues (2006) introduce agent heterogeneity derived from survey results in five different distributions by varying overall/group means and standard deviations of agents' attributes. The result of sensitivity analysis confirms that adding agent heterogeneity can significantly influence the spatial pattern of sprawl and clustering development. Researchers also vary the level of agent heterogeneity and assess its impact on the results. For instance, Chen et al. (2011), found heterogeneity in income can lead to leapfrog development in an exurban area and that exurban development is encouraged when the level of income heterogeneity is more severe.

Although heterogeneous agents are adopted in numerous models, and the effects of agent heterogeneity are emphasized by researchers, comprehensive methods designed to evaluate and understand the effect of agent heterogeneity in a systematic way are rare. In Table 4-4, less than 20% of these models (9 out of 51) have evaluated the effects of agent heterogeneity, although all of them represent agent heterogeneity to some extent. The deficiency in methods for evaluating the effects of agent heterogeneity is magnified when there are multiple sources of agent heterogeneity (i.e. multiple heterogeneous attributes of an agent and/or heterogeneous decision-making processes). As seen from Table 4-4, nearly 65% of models (33 out of 51) have agents with more than one source of agent heterogeneity, but none of them evaluate the effect on outcomes by sequentially adding new sources of agent heterogeneity or increasingly magnify the degree of heterogeneity.

In summary, agent heterogeneity is a double-bladed sword. It is one of the driving forces for residential decision in an urban context. It also introduces additional uncertainties and difficulties in verification and validation of ABMs (Evans, 2012; Manson et al., 2012; Miller et al., 2011). How to appropriately incorporate agent heterogeneity is an important question, which affects the performance of any model. To respond to this challenge an ABM developer should critically reflect on the number of dimensions of attributes' heterogeneity, on the level of agent heterogeneity, and on the interaction among different agent heterogeneity.

4.3.2 Land market representation

A number of researchers have emphasized that the land market should be represented in spatially explicit urban land use models to better explore and simulate the complex interactions between economic systems and natural systems (Haase and Schwarz, 2009; Irwin, 2010; Irwin and Geoghegan, 2001; Ligmann-Zielinska and Jankowski, 2007; Parker and Filatova, 2008). As Parker and her colleagues (2012b) argue, land market factors, ranging from credit availability, interest rates, the strength of demand relative to supply, institutional details of land market, to subsidies, taxes, quotas and insurance, will affect land-use change spatially and quantitatively. Applications of ABM with land market representations are increasing (Chen et al., 2011; Ettema, 2011; Filatova et al., 2011a; Gilbert et al., 2009; Magliocca et al., 2011; Parker et al., 2012a; Parker and Filatova, 2008), and a detailed review is given below.

4.3.2.1 Representations of market processes in practice

To study the impacts of land market representation, Parker et al. (2012b) identify five

market levels ranging from a simple form to a complex structure. As the market level increases, a new land market element is progressively added: locational preferences, resources constraints, competitive bidding, strategic behavior, and endogenous supply decisions. The first three market elements are commonly found in existing spatially explicit ABMs. In addition, endogenous relocation is frequently modeled, even in the absence of land market representation. However, the real relocation processes, the timing and motivation of relocation, are highly related to economic conditions, such as moving cost, employment opportunity, income increase, neighborhood quality (Parker et al., 2012b). Therefore, we regard endogenous relocation as a land market element and compare the differences in representing these four elements across the 51 models (Table 4-4).

Preferences: residential choice is made based on a utility or suitability measuring function. Agents have heterogeneous preferences for properties according to the location, the neighborhood of property and their socioeconomic characteristics. Almost all the models listed in Table 4-4 have functions evaluating the attractiveness of property. Although the final residential choice is based on utility, the methods calculating the utility vary. The Cobb–Douglas function is the most commonly-used functional form in urban economics due to its analytical tractability (Wu and Plantinga, 2003). The preference coefficient in the Cobb-Douglass utility function represents not only the strength of attractiveness of a certain locational attribute but also a share of budget an agent is willing to pay for it. Examples can be found in the models of SOME (Brown and Robinson, 2006), the ALMA series (Filatova et al., 2009a), CHALMS (Magliocca et al., 2011), and HI-LIFE (Fontaine and Rounsevell, 2009). Other methods are also adopted by researchers, such as the Ideal Point decision rule implemented by Ligmann-Zielinska (2009). In this method, the utility is determined by the attractive differences among a

given property, the ideal property and the nadir⁵ property. Another example is the heuristic approach used by (Jackson et al., 2008). In this model, four types of agents choose their properties by different criteria in a decision tree fashion.

Resource constraints: resource constraints mean that buyers' residential choices are restricted by their budgets. In other words, resources constraints reflect the affordability of housing for buyers. Commonly, a buyer agent provides a valuation (WTP) and/or bid price for a specific parcel, which depends on their fixed housing budgets. There are also cases in which their residential choices are indirectly determined by the average income conditions in the neighborhood (Benenson, 1999; Tao et al., 2009). Among all the 51 models, nearly two thirds of them (31/51, 61%) have the component of resources constraints (see Table 4-4). For example, heterogeneous incomes works as a constraint for renting and buying a house in a gentrification model (Jackson et al., 2008; O'Sullivan, 2002), and a driving force causing segregation pattern in residence (Feitosa et al., 2011; Jayaprakash et al., 2009).

Competitive bidding: the sequence of parcel allocation is determined via a competitive bidding process, in which only the buyer providing the highest WTP acquires the parcel. Only 11 models have the competitive bidding process, while 31 models lack it. (Some models didn't describe their parcel allocation method in the publications.) The bidding process allocates properties among agents not only in space but also in time (Chen et al., 2011). It is explicitly defined as a competitive market in which agents make a bid for locations that maximize their utility (Parker and Filatova, 2008). Sometimes it is simulated in an indirect way, for example, as a negotiation process (Ettema, 2011) or an accumulating application process (Li and Liu, 2007).

Relocation is the process by which residents who have settled earlier decide to

5. Nadir means minimum, worst, or bottom

move to another location. In a broad perspective, not only migrating residents who remain in the model, but also residents who leave the system are regarded as relocating agents. It is simulated in 30 (~59%) of the reviewed models (see Table 4-4), although some of them do not model it as an endogenous process and do not involve interactions between relocation and market elements. For instance, in the ABM simulating gentrification process, agents are forced to relocate by economic imperative, namely, when they cannot afford their current places (Jackson et al., 2008), while in most variations of the Schelling's segregation models, agents' movement are driven by increasing dissimilarity of ethnic composition at local neighborhood (Benenson and Torrens, 2004a).

4.3.2.2 Open questions in ABMs with land market representation

Our review reveals that some complex land market elements, such as competitive bidding, are less frequently incorporated in models (see Table 4-4). The objective of any model is to, on the one hand, replicate the real situation as precisely as possible, and on the other hand, keep the model as simple as possible. The tradeoff between the simplicity of the model and robustness of results gives rise to the open question: do the effects of diverse land market elements contribute to improving the validity and robustness of model (Huang et al., in review; Sun et al., in review). Meanwhile, researchers argue that different elements of market representation could significantly influence both the complexity of a model and its spatial and economic outcomes (Polhill et al., 2007). However, to our knowledge, there is no research systematically investigating how all these market elements affect the spatial and economic patterns and trajectories of land use change. The open question is how to evaluate the effects of diverse land market elements in the design of an ABM and concomitant experiments.

Additionally, as more land market elements are simulated in the model, the implications of a much broader range of policies, especially economic policies, can be tested in the model, which will potentially provide insightful information to support decision-making of planners and stakeholders. The open question is how to ensure the transparency of land market processes as well as the reliability of output to their decisions.

4.3.3 Measurement of outcomes

Relative to simpler modeling methods, ABM brings another dimension of outcomes because it can simulate the decisions and behaviors of individual agents and consequent emergent patterns. Meanwhile, random processes are incorporated in the simulation of agents. Collectively, these dimensions pose a greater challenge in measuring model outcomes.

4.3.3.1 Landscape-level and aggregated-level outcomes

Traditionally, urban land-use models provide spatial outcomes of land use composition and pattern, and socioeconomic outcome at a landscape or an aggregated level. These outcomes are further analyzed to validate the model and provide projections under “what-if” scenarios. Spatial metrics, which stem from landscape ecology in the late 1980s and are based on a categorical, patch-based representation of a landscape, are the most common method for analyzing spatial patterns (Herold et al., 2005). About 85% of the models (43 out of 51) use spatial distributions or landscape metrics to analyze their results, for example, the measure of fragmentation and land use diversity caused by externalities in urban ABMs (Brown et al., 2004a; Parker and Meretsky, 2004), or the measure of segregation by income or cultural/ethnicity identity (Benenson, 1998; Fossett

and Waren, 2005; Jayaprakash et al., 2009; Omer, 2005; Schelling, 1971).

4.3.3.2 Individual-level outcomes

At the same time due to agent heterogeneity and land market representation urban residential choice ABMs provide process-based results and socioeconomic outputs at the individual level, such as individual transaction prices, social welfare and bidding history. This additional information also has the potential to play an important role in model verification, validation, and result analysis (Evans, 2012; Ngo and See, 2012). It also has the ability to enrich our understanding of the complex processes of land-cover and land-use change (LUCC) and their consequences. For instance, the detailed trajectories of LUCC at the agent level can be used to explore the path-dependent process of residential choice. However, only 7 models⁶ (14%) use individual information in their analysis, and only 9 models⁷ (18%) use economic results to validate a model's performances. Examples include the rent map and curve used by Caruso et al. (2007; 2009; 2005) and the regression analysis used by Xie et al. (2007). Therefore, how to analyze the broad dimensions of outcomes at the agent level is a challenge yet to be overcome.

4.3.3.3 Stochasticity and repetitive runs

Incorporation of intelligent adaptive agents in a model adds more random and stochastic factors and processes. Researchers find it unreliable to measure the output based on a single run of model under a given parameter settings. Repetitive model runs are required to assure that an outcome is stable irrespective of different random seeds (in LUXE, the

⁶ Model No. 7, 11, 18, 19, 35, 42, 51 in Table 4-4

⁷ Model No. 11, 16, 17, 18, 21, 26, 32, 41, 42 in Table 4-4.

random seeds are used to initialize budget and preference heterogeneity). Therefore, modelers use different approaches to retrieve information from repetitive runs. The most straightforward method is to use the averages and variances of outputs after repetitive runs (Brown and Robinson, 2006; Crooks, 2010; Ettema, 2011; Magliocca et al., 2011; O'Sullivan et al., 2003; Zellner et al., 2010). Another common method is using a formal sensitivity analysis (Caruso et al., 2007; Jackson et al., 2008; Kii and Doi, 2005; Ligmann-Zielinska and Jankowski, 2010; Ligmann-Zielinska and Sun, 2010; Loibl et al., 2007; Loibl and Toetzer, 2003). Statistical tests, such as t-test (Filatova et al., 2009a; Filatova et al., 2009b; Wasserman and Yohe, 2001) and ANOVA analysis (Sasaki and Box, 2003), are also conducted to confirm the stability of outcomes. However, there is no agreement on either the criteria determining the number of repetitive runs or a method of analyzing the outcomes of repetitive runs.

4.4 Conclusion and discussion

This chapter provides an overview of functionalities brought by ABM to simulate urban residential choices, with specific attention to agent heterogeneity, land market representation and measurement of outcomes. Following the continuum from theoretical to empirical, the 51 models reviewed in this chapter can be generally divided into three categories: classical models extended using ABM, models simulating different stages of urbanization process, and integrated ABM-MSM models. Their features are summarized and compared within each category of models.

Three distinctive features stemming from the ABM technique are reviewed and discussed in detail. The first one is agent heterogeneity. Agent heterogeneity is introduced into a model by changing either agents' attributes or their decision-making rules. However, the insufficiency of methods to evaluate the effects of agent

heterogeneity on the outcomes of urban dynamics/patterns might be a challenge in guaranteeing the validity of simulation results. The second feature is the level of land market representation, which can be gradually increased by adding resource constraints, competitive bidding, and endogenous relocation upon a residential choice driven by preferences only. Among the four elements reviewed here, preferences are the most commonly represented element, while competitive bidding is the least. Resource constraints and endogenous relocation are less popular than preferences, and the implementation of endogenous relocation usually does not represent the direct interaction between household and land market. The necessity and the methods of assessing the effects of diverse land market representation on the outcomes will be a priority area of study when incorporating land market elements in an ABM. And the last feature of interest for this review is methods to analyze macro and micro level outcomes of an ABM. Traditional measurements, such as spatial metrics alone, are not sufficient to study an ABM outcome. It is necessary to use a wider range of methods, metrics including individual level observations to study and visualize outputs, and to verify and validate models.

Urban land-use models can benefit from ABM by incorporating heterogeneous intelligent agents and explicit modeling of an institution that stands behind land exchange (i.e., land market representation in this case). However, the flexibility of modeling technique and consequent broader dimension of outcomes will also bring considerable challenges.

First, the tradeoff between the simplicity of the model and the ability to replicate complex human-environment interactions in urban context provide a great challenge for researchers. In the landmark book, *Models in Geography* (Chorley and Haggett, 1967), models are defined as “selective approximations designed to elucidate fundamentals; pattern-seeking or structured; suggestive or speculative instruments, which were

experimentally fertile in suggesting further questions; analogies; constructional stepping stones to the building of theories and laws – not to be tested as true or false, but as appropriate, simulating and significant; and finally, cognitive – promoting the communication of scientific ideas” (page 22-24). As such, a model is an abstract simplification and representation of real world rather than a complete replication of reality. Thus, the important question is whether these features (e.g., agent heterogeneity, land market representation) brought by ABMs are essential and necessary for simulating urban residential phenomena (O’Sullivan et al., 2012). In other words, the decision to include agent heterogeneity or land market elements depends on whether the nature of urban residential patterns needs to be captured by a setting of heterogeneous agents and presence of land market institution, and whether the final results will be significantly biased or conflicting when agent heterogeneity or a land market is missing.

Second, when more features are simulated in the model, representing the interactions within each feature and between features poses another challenge. As discussed in Section 3.1, agent heterogeneity suggests agents may vary in multiple attributes and their decision-making rules. The interaction within multiple sources of agent heterogeneity and, between agent heterogeneity and land market representation, is complex and nonlinear. It can potentially lead to unexplored effects (Huang et al., in review). The exploration of nonlinearity, complexity, and sensitivity, therefore, need to be conducted beforehand to confirm the reliability of a model (Parker, in review; Parker et al., 2002).

The third challenge is the conflict between the demand for the data at the individual level and scarcity of available data (Batty et al., 2012). Agent heterogeneity raises a strong demand for the data at individual or household level, which are relatively rare in historical records and census. Sometimes its representation requires conducting extensive surveys, role-playing games or laboratory experiments to collect behavioral data. The uncertainty within the data and the inconsistency between observed pattern and stated

preferences in surveys place another obstacle in simulation ([Evans, 2012](#)). Moreover, as ABMs generate output data at both macro (e.g., aggregated spatial patterns and socio-economic measures) and micro levels (e.g., changes in individual welfare, evolution of individual decisions rules or opinions) across multiple dimensions (e.g., spatial, economic, demographic), new methods of measuring, visualizing and communicating these outputs are in great need ([Grimm and Railsback, 2012](#); [Parker et al., 2003](#)).

Chapter 5 Effects of agent heterogeneity in the presence of a land-market: a systematic test in an agent-based laboratory

5.1 Introduction

Land-use and land-cover change (LUCC) in the context of an urban environment is the result of the dynamics of coupled human and natural systems. Agent-based models (ABMs) have advantages in simulating the complexity (e.g., nonlinearity, path-dependence, heterogeneity, and emergence) in these systems and integrating empirical findings from multiple disciplines (e.g., geography, sociology, economy, and psychology) (Batty, 2005; Liu et al., 2007). For these reasons, both theoretical and empirical ABMs have been developed to simulate urban LUCC (Clifford, 2008; Liu et al., 2007; Matthews et al., 2007; Parker et al., 2003; Robinson et al., 2007).

One of the essential advantages of ABM is its ability to connect heterogeneous individual decision-making processes with emergent spatial patterns. In fact, empirical studies show that the heterogeneity among agents, including preferences for amenity, risk perceptions, income differences, demographic and household characteristics and different strategies of land development and management, plays a pivotal role in determining spatial landscape patterns and socioeconomic outcomes (Brown & Robinson, 2006; Ghoulmie et al., 2005; Ligmann-Zielinska, 2009; Magliocca et al., 2011). In addition to agent heterogeneity, representations of land-market processes, for example, preferences, budget constraints, and competitive bidding, are important factors in bridging the gap between rigorous spatial dynamics models and existing ABMs that omit these components (Irwin, 2010; Parker et al., 2012b).

Although agent heterogeneity and market representation are main components in modeling urban LUCC, the effects of agent heterogeneity under various land market representation have not been systematically inspected (Irwin, 2010; Parker et al., 2012b; Parker and Filatova, 2008). The deficiency lies in several aspects. First, few models incorporate market process. Second, even though almost every ABM has agent heterogeneity to some extent, few studies have systematically tested the effects of continuous variation in the magnitude of agent heterogeneity on the output, especially in a model that has land market mechanisms (Parker et al., 2012b). Moreover, several studies come to conflicting conclusions regarding the effects of agent heterogeneity on projected land-use patterns (more details in Section 5.2.3). Third, the interactions between multiple sources of agent heterogeneity are overlooked since most of models treat agents with a single heterogeneous characteristic.

Using a stylized Agent-based land market model (ABLMM) named LUXE (Land Use in eXurban Environments), which simulates residential choices under different levels of market representations, we systematically investigate the multidimensional effects of agent heterogeneity on spatial and socioeconomic patterns of land-use change. In our model, there are two sources of agent heterogeneity. One is income heterogeneity, which imposes constraints on the affordability of buying land; the other is preference heterogeneity, which influences locational choice. Landscape measures (e.g., edge density) as well as socioeconomic measures (e.g., evenness index) are used to analyze the spatial patterns of land use and land price. The innovation of this chapter is to comprehensively explore the effects of agent heterogeneity in an ABLMM. The findings could potentially provide insights on the design of ABMs as well as reconcile some conflicts in the outcomes of existing ABMs.

To meet this goal, we address four research questions: *(1) How does agents' heterogeneity in incomes or in locational preferences affect emergent land-use patterns?*

(2) How does the magnitude of heterogeneity in the agents' population affect spatial and economic phenomena? (3) Do the collective effects from multiple sources of agent heterogeneity vary under different market representations? and (4) Are different representations of market elements able to reconcile some conflicting results about the effects of agent heterogeneity drawn by other models? The chapter is organized in the following way. Section 5.2 provides an overview on modeling agent heterogeneity and land markets with ABMs. Section 5.3 presents the stylized ABLMM and the settings for the experiments designed to explore the effects of agent heterogeneity under four market representations. In section 5.4, results of different experiments are compared. Finally, section 5.5 provides the general conclusion and discussion.

5.2 ABM and Heterogeneity: A brief overview

Spatially explicit ABM is widely used for simulating complex urban land-use change phenomena, including residential choice (Brown, et al., 2008; Kii and Doi, 2005; Ligmann-Zielinska, 2009; Torrens, 2007), social-economic segregation (Benenson, 1998; Benenson, Omer, & Hatna, 2002; Crooks, 2006; Feitosa et al., 2011; Fossett and Waren, 2005; Jayaprakash et al., 2009; O'Sullivan et al., 2003), gentrification (Diappi and Bolchi, 2008; Jackson et al., 2008; O'Sullivan, 2002), verification of location theory (Sasaki and Box, 2003), zoning and urban planning (Ligtenberg et al., 2004; Zellner et al., 2010), the housing market (Ettema, 2011; Filatova et al., 2009a; Filatova et al., 2009b; Magliocca et al., 2011; Parker and Filatova, 2008) and microsimulation of urban systems (Ettema et al., 2007; Kii and Doi, 2005; Miller et al., 2008; Miller et al., 2011; Waddell, 2002; Waddell et al., 2008; Wagner and Wegener, 2007). Agent heterogeneity plays an important role in these models.

5.2.1 Heterogeneous economic agents

In a spatial land market model, agent heterogeneity refers to the differences among either characteristics of individual decision makers (e.g., preferences, incomes) or their behavioral functions (e.g., expectations formation, decision-making strategies). The differences could be either internal (e.g., demographic and household characteristics, personal experiences, expectations, and risk attitudes) or external (e.g., social networks, accessibility to information, and policies) (Irwin, 2010; Valbuena et al., 2008). Generally speaking, two approaches are used to introduce agent heterogeneity at model initialization (Brown and Robinson, 2006). The first method is to continuously vary the agent characteristics (e.g., income or preference). For example, Benenson (1999) found continuously varying economic characteristics (e.g., income and income growth rate) will result in a relatively stable residential distribution. Filatova et al (2011a) found qualitatively different results in spatial and economic metrics in hazard-prone areas between households with heterogeneous risk perceptions based on an empirical survey distribution and homogeneous agents with risk perception equal to the average of the population.

The second method to impose heterogeneity is to divide the agents into different categories. The typology of agents could be determined by either one attribute (e.g., ethnicity) or multiple criteria (e.g., income level and neighborhood circumstance) (e.g., An, 2012). Different groups of agents could share the same decision-making function but have different parameters for the function, or they could even have different decision-making strategies. For example, Li and Liu (2007) divided households into five groups and empirically calibrated their weights on the same utility function. Satisfactory results of residential development were produced by a few groups of agents. Ghoulmie and colleagues (2005) found, in a single-asset financial market that heterogeneity of agent strategies is one of the important ingredients in reproducing some regular patterns.

Magliocca et al., (2011) also used different decision making processes for developers in the formation of rent expectations and suggested the path dependence of spatial patterns has direct linkage with individual heterogeneity.

5.2.2 Agent heterogeneity in an agent-based land market models

Classical analytical land-market models such as the Von Thünen model (Von Thünen, 1966) and the monocentric city models (Alonso, 1964; Mills, 1972; Muth, 1969) established theoretical benchmarks for economic models of urban land-use change, e.g., the downward-sloping rent gradient, which is also seen robustly in the real world. Such analytical models, however, are of limited utility for examining spatial and actor-level heterogeneity in combination. In response, the usefulness of spatially explicit ABMs that contain land market representations has been emphasized by reviews (Haase and Schwarz, 2009; Irwin, 2010; Irwin and Geoghegan, 2001; Ligmann-Zielinska and Jankowski, 2007; Parker and Filatova, 2008); however, ABMs that have a representation of an explicit land market remain relatively rare. A subset of these models has enabled researchers to extend these classical models to directly simulate individual's behavior in a land market, replicating the classical results as a model verification exercise (Chen et al., 2011; Filatova et al., 2009b).

The importance of ABLMM in understanding the effects of agent heterogeneity on the processes and patterns of LUCC can be summarized in several aspects. First, ABLMM provides a more flexible platform that needs fewer assumptions and restrictions compared to traditional economic models. As discussed in greater detail in Section 5.2.3, models can embrace agent heterogeneity rather than use a representative agent, and focus more on the out-of equilibrium dynamic rather than on the equilibrium per se (Arthur, 2005; Hommes, 2005; Kirman, 1992; Tesfatsion, 2006). Second, in addition to the

aggregated spatial patterns and economic metrics, ABLMM generates heterogeneous information at the individual level (e.g., agent's preference and pricing information). This additional information can provide various measurements (e.g., segregation index, sprawl measurement, and rent gradients) to compare with empirical findings or theoretical studies and enrich our understanding of the process of LUCC and its consequences. Third, it serves as a laboratory to test some hypotheses about effects of agent heterogeneity in land-use simulations. On the one hand, empirical data can be used in an ABLMM to replicate the LUCC trajectory; on the other hand, theoretical models can help researchers find out what kinds of data should be collected to parameterize empirical information into the model.

We identify three critical elements of the land-market process: preferences, budget constraints, and competitive bidding (Parker et al., 2012b). Building upon these three, Table 5-1 divides the market mechanisms into four levels, and then compares the market representations and agent heterogeneity realized in the representative models mentioned above.

- In market level 0, agents make residential choice based on preferences without budget constraints or competitive bidding. Representative applications are the SOME model developed by Brown et al. (2004a; 2006) and the model developed by Benenson et al. (1998; 1999). The agents are potentially heterogeneous in their preference for residential density in the former model, and in the latter model their budgets are potentially heterogeneous.
- In market level 0.5, competitive bidding is added. A representative model is developed by Ligmann-Zielinska (2009), which simulates the developer's bidding behavior with heterogeneous risk attitudes.
- Budget constraints for buyers are represented in market level 1. The

geographic automata model developed by Torrens (2007) is an example.

- In the last level, market level 2, both competitive bidding and budget constraints are included. The ALMA-C (Filatova et al., 2009b) model and CHALMS model (Magliocca et al., 2011) have the functionality to simulate both mechanisms.

It is evident that the market representations are different for these representative models. However, none of these models is able to fully examine the effects of agent heterogeneity across all these market representations.

Table 5-1 Agent heterogeneity and market levels in representative models

Market level	Bidding	Budget constraint	Agent heterogeneity		Representative models
			Preference	Budget	
L0	No	No	No	No	Standard CA
			Yes	No	SOME, Brown et al. (2004a; 2006), Zellner et al. (2010)
			No	Yes	Benenson et al. (1998; 1999)
L0.5	Yes	No	No	No	(Ligmann-Zielinska, 2009)
			Yes	No	(Ligmann-Zielinska, 2009)
L1	No	Yes	No	No	CA model with threshold of land use change
			Yes	Yes	GA (Torrens, 2007)
L2	Yes	Yes	No	No	CA model with multiple land uses
			Yes	Yes	ALMA-C (Filatova et al., 2009b); CHALMS (Magliocca et al., 2011)

5.2.3 Effects of agent heterogeneity

The ability to incorporate agent heterogeneity is one of the main reasons why ABM is attractive to both economists and geographers. For economists, an ABM provides a platform that could relax the assumptions and restrictions on traditional economic models (Arthur, 1999, 2005; Tesfatsion, 2006). Traditional economic models usually adopt a representative agent and assume a static equilibrium condition. However, in real conditions, agents are inherently different in their demographic and socioeconomic characteristics and therefore have different actions, strategies and expectations in their decision-making (Arthur, 2005; Axtell, 2000, 2003; Epstein, 1999; Farmer and Foley, 2009; Hommes, 2005; Tesfatsion, 2006). Substitution of heterogeneous agents by a representative one in a model may result in failure to simulate realistic macro-pattern and misrepresent the response to a policy measure (Kirman, 1992). Counter-intuitively, in some cases, an increase of agent heterogeneity has the effect of producing regular and stabilizing results. In Kirman's review (1992), an increase in the heterogeneity of income or preference may give rise to a smooth aggregated demand pattern. For geographers, an ABM provides a more powerful tool to simulate the heterogeneous interactions between human and natural system than traditional modeling approaches, which have not represented decision makers. Unlike CA models, which solely rely on the historical and neighborhood spatial heterogeneity, ABMs introduce heterogeneous decision makers (Macy and Willer, 2002). Increasingly, researchers have found that the agent heterogeneity is a driving force for landscape change. By allowing the inclusion of agent heterogeneity, emergent landscape pattern and LUCC phenomena can be simulated from the bottom up, for example, urban sprawl, urban gentrification, residential segregation, and locational choice of residents and firms (Benenson & Torrens, 2004a).

Even though the importance of agent heterogeneity is emphasized by researchers, systematic investigations of the effects of agent heterogeneity are rare. This gap is

important for various reasons. First of all, most existing models have a single heterogeneous characteristic and focus on either spatial or socioeconomic outcomes. In reality, however, agents differ from each other in several characteristics, each of which might have similar effects. For instance, heterogeneous preferences for open space amenities, lifecycle events and income heterogeneity could lead to leapfrog and fragmented patterns (urban sprawl) as well as income segregation (An et al., 2010). Further, using only one heterogeneous characteristic excludes the interactions between different heterogeneous characteristics. Studies show the collective effect of multiple sources of agent heterogeneity affects the performance of model substantially. For instance, in the segregation model, Benenson (1999) found variation of economic status and cultural diversity have complicated effects on the stability and segregation of cultural groups. In a land-market model, Magliocca et al. (2011) found interactions between heterogeneity in preference for housing types and income will lead to sprawling development in an ex-urban area.

Second, the effects of magnitude of agent heterogeneity on model outcomes are uncertain. For instance, Brown and Robinson (2006) used the SOME model to show that the presence of preference heterogeneity will lead to more sprawl regardless of the magnitude of preference heterogeneity. In contrast, Ligmann-Zielinska (2009) found the preference for specific criterion (e.g., attractiveness or price) has dominant effect on the spatial distribution of development, and the levels of compact development are significantly different when the representative developer changes his risk attitude. But the effects are negligible when there are multiple developers with combinations of heterogeneous risk attitudes. The open question is, does the spatial pattern vary monotonically with an increased magnitude of agent heterogeneity, or do multiple sources of agent heterogeneity have nonlinear effects on the outcomes?

Third, inconsistent conclusions on the effect of agent heterogeneity are drawn by

different models. For example, Brown and Robinson (2006) have used survey data in the SOME model to show that adding preference heterogeneity to agents will result in more sprawling and fragmented development. However, in a latter study based on the same model, Zellner et al. (2010) found that the effect of incorporating heterogeneous preference is not uniform. More specifically, heterogeneity will induce compact development when most households have higher preference for density but sprawling development when the mean of density preference is low. Using another model, Ligmann-Zielinska (2009) found the land-use pattern is slightly less compact when the developers have heterogeneous risk attitudes. Filatova et al. (2009b) found that agents' heterogeneous risk attitudes will lead to more developments in a coastal area that has higher level of amenity and is far from city center even under budget constraint and competitive bidding. It is clear that these conflicting conclusions are drawn by different models with different representations of market processes (Table 5-1). Evaluating the effect of agent heterogeneity across different levels of market representation gives us opportunity to reconcile these inconsistent conclusions.

In summary, although most researchers agree on the importance of agent heterogeneity and represent it to some extent, the effects of varying multiple sources of agent heterogeneity are not systematically inspected, and the conclusions drawn are inconsistent. In addition, a considerable number of models have more than one source of agent heterogeneity. The open question now is to what extent the agent heterogeneity, magnitude of agent heterogeneity, and interaction of multiple sources of agent heterogeneity (e.g., budget and preference) will affect spatial and socioeconomic outcomes. A corollary question is whether differences, if found, can reconcile the inconsistent conclusions drawn by different models with market representations. Our stylized ABLMM, LUXE, provides the opportunities to explore these research questions through its ability to accommodate multiple sources of agent heterogeneity and to

evaluate the effects across different levels of market representation at the aggregated level and individual level.

5.3 Model description and scenario setting

The LUXE model belongs to the SLUCE II (Spatial Land Use Change and Ecological Effects) project, which is a part of a larger modeling effort that integrates land-use and land-management dynamics as well as ecosystem services processes (Robinson et al., in press). A more detailed description of the model can be found in Parker et al.⁸ (2012b).

5.3.1 Model description

Space in LUXE is divided into a rectangular lattice of congruent cells. Each cell is either agricultural land or residential land. There is a CBD centered in the lattice. No other public facilities, i.e. road network, school, or hospital, are represented.

Two types of agents are simulated in the model. Sellers are the owners of land who put their lands in the market, receive and evaluate a number of bids from buyers, and sell the land to the highest bid, provided it is larger than their expected prices (i.e., willingness to accept, WTA). The second type of agents are buyers, who are households looking for residential land. Every buyer evaluates a number of parcels and forms a utility based upon spatial characteristics and individual preference given by a Cobb-

⁸ The model is coded in Java and developed in the Eclipse platform, mainly by Dr. Shipeng Sun. I contributed to the testing and debugging of the model.

Douglas form⁹:

$$U = A^\alpha \cdot P^\beta \quad (5-1)$$

where U denotes utility; A stands for measure of open space amenity, which is the residential density in a Queen's neighborhood¹⁰. The residential density is the reciprocal of the number of developed parcel in the defined neighborhood. It is further normalized to a range from 0 to 1. α and β are the weights for A and P respectively and $\alpha + \beta = 1$. P is the proximity to the CBD. It can be calculated as:

$$P = (d_{\max} - d) / d_{\max} \quad (5-2)$$

Where d_{\max} is the maximum distance of development (it is 30 because the size of the landscape is 61, see Table 5-2), d denotes the distance from the parcel to the CBD measured in Euclidean distance. Therefore, when a parcel is developed at the edge of the landscape, its P value is 0; whereas it is developed in the center, its P value is 1.

Buyers form their ask price (willingness to pay, WTP) based on the utility and available budget and transport cost (Filatova et al., 2009a).

9 LUXE combines the features of two existing models, ALMA and SOME, which are also based on the Cobb-Douglas form of utility calculation. The Cobb-Douglas functional form is a standard in economics, allowing easy comparison to other work. However, the form has acknowledged limitations, such as optimally allocating a fixed share of the buyer's budget to each good, regardless of their income level. In this model, the buyer's willingness to pay reflects their demand for a bundle of goods' attributes — proximity and amenities. In the real world, relative expenditures to these two factors might vary as income increases or decreases. Therefore, although we used the Cobb-Douglas functional form here to maintain comparability to previous work, some results of the effect of budget heterogeneity might be modified using a more flexible functional form. This would be a valuable extension for future work.

10 In this model, the neighborhood size is set to 2 (i.e. nearest 24 neighbors surrounding a host cell in a 5 by 5 neighborhood), because a neighborhood size larger than 2 is prone to induce a fragmented landscape and smaller ones encourage infill development. This neighborhood size results in a checkerboard pattern around the periphery of city (Fig. 5-1). This pattern will be more compact if the size is 1 or more sparse if the size is larger than 2.

$$WTP = (B - t \cdot d) \frac{U^2}{b^2 + U^2} \quad (5-3)$$

where B stands for the individual budget, and $t \cdot d$ is the transport cost to the CBD, which is a linear function of d , the distance to the CBD, and t , the transport cost per unit of distance, is set to 1. U is the utility from equation (1) and b is a constant that represents the affordability of all the other non-housing goods. The chosen WTP function is consistent with the previous ALMA model (Filatova et al., 2009a) and reflects the main qualitative properties of the neoclassical demand function.

The model starts with initialization of the CBD at the center of the space. Sellers are initialized with a fixed and homogenous WTA for every cell. Then a number of buyers are generated with potentially heterogeneous budgets and preferences. All sellers put their properties on the market, and buyers evaluate all the properties and bid on the one with the maximum utility. This implies the buyer will bid on the most desirable cell over the whole space. Sellers receive a number of bids via the market and decide whether to accept or reject the bid based on different rules under different market levels (explained in 5.3.2). A successful transaction is registered if the seller agrees to sell the parcel, and the land cell is then converted to residential. In this case, the transaction price is equal to buyer's WTP. Failed buyers re-enter the market at the next step. Thus, each run of model may contain multiple steps. Finally, a market clearing condition is reached when no more transactions can be made. Essentially, this final result replicates a static economic equilibrium in the land market.

5.3.2 Market levels

In order to explore the effects of agent heterogeneity under different market representations, four levels of market representations are designed (see Table 5-1). The parameter setting for each market level is explained in Table 5-2.

Table 5-2 Key input parameters for the LUXE model

Parameter	Meaning	Values
<i>Constant Parameters</i>		
S_L	size of the square landscape	61
N_b	number of household buyers	400
N_s	number of rural land sellers	3,721(61 by 61)
$\delta\beta$	the range of β utility calculation, beta will be bounded by $[\beta - \delta\beta/2, \beta + \delta\beta/2]$	0.75
b	Budget splitting factor	0.6
t	unit transport cost	1.00
\bar{B}	mean housing budget for buyers	160
r_N	the size of a rook neighborhood in the calculation of open space amenity	2
$\bar{\beta}$	mean value of preference for proximity in utility calculation	0.5
N_{sp}	the number of parcels that a buyer evaluate for bidding	4000
C	whether the central parcel should be considered in calculating open space amenity in the neighborhood	false
<i>Market level Parameters</i>		
WTA	Agricultural reservation price	0, 100
N_{bd}^{\max}	number of bids allowed for one parcel, one means no bidding	1, 400

Note: market level 0: WTA=0 and $N_{bd}^{\max}=1$; market level 0.5: WTA=0 and $N_{bd}^{\max}=400$; market level 1: WTA=100 and $N_{bd}^{\max}=1$; market level 2: WTA=100 and $N_{bd}^{\max}=400$.

In order to control the randomness in the model, all the buyers in the model have complete information of the land market. That means, buyers will evaluate all the parcels and bid on the one with the highest utility ($N_{sp} > N_s$). In market level 0.5 and 2 (with the market element of competitive bidding), the N_{bd}^{\max} is equal to N_b , it means that sellers can receive at maximum of 400 bids and choose the highest one in case all the buyers compete for one parcel.

- Market level 0 (L0) is the most primitive scenario, without budget constraints and competitive bidding. Therefore, the agricultural reservation price (WTA) and number of bids allowed for one parcel are set to 0 and 1 respectively. In

other words, each buyer in market level 0 will sequentially choose the parcel with the highest utility in a first-come first-serve way.

- In market level 0.5 (L0.5), competitive bidding is added but a budget constraint is still missing. It implies that the buyers can compete for the same parcel, and the one with the highest bid will get that parcel.
- In market level 1 (L1), a budget constraint is added, but competitive bidding is suppressed. That means that buyers will only get the parcel if their WTPs are higher than sellers' fixed WTA.
- Both competitive bidding and budget constraints are represented in market level 2 (L2). This implies that buyers will bid on the land, and the seller will accept the highest bid only if the maximum bid is larger than the WTA.

Under the four market representations, we design three series of experiments to answer the three questions mentioned above with regard to the effects of agent heterogeneity on the spatial and socioeconomic outcomes.

5.3.3 Model setup

Table 5-2 lists all the parameters used in the experiments for this study. Experiments are carried out in a square lattice of 61×61 cells¹¹ initially. Every cell is occupied by a seller, and therefore there are 3721 sellers. The number of buyers is 400 at model initialization. Their budgets and preferences are set according to their mean and standard deviations under different experiments (see section 5.4 for details). In order to guarantee that the experiments with heterogeneous agents are comparable to the ones with homogeneous agents, the preference and budget follow a stochastic distribution with equal mean values but different standard deviations.

5.3.4 Model validation

The goal of validation is to compare the model outcomes to independent data and expectations and to measure the agreement between them (Manson from Parker et al., 2002). ABMs face some challenges in model validation (Manson, 2002; Ngo and See, 2012; Parker et al., 2002). One of the reasons is that the agents in ABMs can inherently

¹¹ Our goal in setting the landscape size was to choose a landscape that was sufficiently large for robust experimentation, but small enough to maintain computational tractability. We determined that the 61×61 cell landscape is sufficiently large because: 1) Recalling that this is essentially an open city model, all buyers who wish to purchase parcels in each run are able to locate (equivalently, the landscape is large enough to reach equilibrium). 2) The range of urban development in each equilibrium is well within the landscape boundary, causing no edge or boundary effects. 3) Under current parameter settings with 400 buyers, no buyer would choose a cells beyond their current range as it would invoke a higher transport cost. 4) although the actual pattern metrics would differ slightly in a larger landscnaape due to smoothing effects, the standard deviations of all these metrics across 40 repetitive runs are relatively small (Table 5-4), which indicates the results are stable and sufficient to represent the individual-level processes that drive land transition with agent heterogeneity. 5) Finally, the standard deviations of socioeconomic metrics are also small, and the number of observations is sufficient to provide econometric rent gradient estimates with high significance levels and goodness of fit.

evolve over time and space, which means it is impossible to validate the outcomes with another independent data set (Crooks et al., 2008).

Manson (2002) divided validations into two types: structural validation and outcome validation. Structural validation measures how well the model represents the theoretical mechanisms of real-world phenomenon (Manson, 2002). In LUXE, structural validation is performed by replicating the classical outputs of monocentric model (i.e., a downward slope of land prices from the urban center, see the first column of Figure 5-8), similar to the ALMA model (Filatova et al., 2009a). In addition, a large range of input parameters are swept by me and another SLUCE team members (Sun et al., in review) separately to guarantee that model outcomes are consistent with theoretical expectations. In this stage, the agreement between model outcome and theoretical patterns are measured by qualitative and visual interpretation.

Outcome validations measures how well the model outcomes conform to empirical data (Manson, 2002). Current the LUXE model is a highly stylized ABM, with no empirical content. Therefore, outcome validation is not relevant at this stage off modeling. However, the final stage of SLUCE II model will be equipped with empirical data. It can be validated by comparing model outcomes to real-world data in both spatial and nonspatial dimensions, for example, quantity and patterns of land-cover change, land-management change, land and housing prices, and carbon exchange and storage, which also suggests that the output validation requires extensive data from census, remotely sensed images, household surveys and field surveys (e.g., Miller et al., 2011).

5.3.5 Output measurement

Traditionally, spatial land-use change model outcomes are analyzed by landscape metrics, which are derived from landscape ecology and used for measuring landscape patterns,

such as fragmentation metrics, diversity metrics (Brown, et al., 2004a; Irwin and Bockstael, 2002; Parker and Meretsky, 2004), and segregation metrics (Benenson, 1998; Fossett and Waren, 2005; Jayaprakash et al., 2009; Omer, 2005; Schelling, 1971). However, a land market model can provide economic as well as spatial outcomes. Hence, two groups of metrics are used to evaluate the model outcomes¹². The first group includes three landscape metrics, which measure the spatial patterns of land use change. First, the total developed parcels (TDP) records how many parcels are converted from agriculture to urban land. Second, edge density (ED) measures the edge characteristics of land-use change. It varies from 0 to 1, and a smaller value indicates a more compact pattern. Mean transport cost (MTC) indicates the average range of urban development.

The second group of metrics concerns socio-economic patterns at the agent level. Mean transaction price (MTP) and mean utility (MU) measure the land price and satisfaction of agents at an aggregated level. An evenness metric, the Theil index (Theil, 1967), is used to measure wealth inequality (i.e. budget in the model). The Theil index is calculated as:

$$Theil = \frac{1}{N} \sum_{i=1}^N \left(\frac{x_i}{\bar{x}} \cdot \ln \frac{x_i}{\bar{x}} \right) \quad (5-4)$$

where x_i is the budget for agent i , and N is the number of final transactions, and \bar{x} denotes the mean budget of all these transactions. This index varies from 0 to $\ln N$, where 0 indicates a equal distribution of income and $\ln N$ indicates the maximum inequality, with one buyer having all the income. This index measures the evenness of budget for all the successfully transactions. Therefore it will not vary between market levels L0 and L0.5 since all the buyers can find a parcel. But it will change in market levels L1 and L2 because only some buyers can afford a parcel under their budget constraints.

12 These metrics, as well as Figures from 5-2 to 5-8 are generated by the original outputs of the model by R scripts.

Furthermore, due to the random process and uncertainty in the model, 40¹³ repetitive runs are used to generate outcomes for each parameter setting to guarantee the stability of results. The results of metrics are reported by their mean and standard deviation values.

5.4 Experiments and results

Three series of experiments are designed to explore the effects of multiple agent heterogeneity across the four market levels. Table 5-3 lists the parameters for the three experiments. The first experiment is designed to explore the first question: *How does agents' heterogeneity in incomes and in locational preferences affect emergent patterns?* The results are compared between homogeneous agents and agents with either heterogeneous budgets or heterogeneous preferences (i.e. when agents have heterogeneous budgets, their preferences are fixed and vice versa). The second experiment is designed to answer the question: *How does the degree of heterogeneity in agents' population affect spatial and economic phenomena?* More specifically, *do the spatial and socioeconomic outcomes vary monotonically with the increasing degree of agent heterogeneity?* Like the previous experiment, only one type of agent heterogeneity (either budget or preference) is changed while the other one remains constant. However, a broader magnitude of heterogeneity is investigated. Specifically, five gradations of heterogeneity in budget or preference are analyzed by gradually increasing the standard deviations of budget or preference (Table 5-3). Unlike the former two experiments, the

13 The rationale choosing 40 repetitive runs is, on the one hand, to guarantee the standard deviations of the six metrics are small and relatively stable (see Table 5-4 for standard deviations of each metric across 40 runs), and on the other hand, by referring to the experience on developing two existing ABMs in the same project group (i.e., SOME and ALMA).

last experiment changes budget heterogeneity and preference heterogeneity simultaneously. The collective effects of multiple sources of heterogeneity are compared to answer the question: *Do the collective effects from multiple sources of agent heterogeneity vary under different market representations?* By analyzing the results across the four market levels, the findings will be able to answer the question: *Is the representation of market elements able to reconcile some conflicting results about the effects of agent heterogeneity drawn by other models?*

Table 5-3 Values of the parameters in the three experiments

	Standard deviation of preference for proximity	Standard deviation of budget
Experiment 1	0	0
	0	30
	0.3	0
Experiment 2	0.1, 0.2, 0.3, 0.4, 0.5	0
	0	10, 20, 30, 40, 50
Experiment 3	0.1, 0.2, 0.3, 0.4, 0.5	10, 20, 30, 40, 50

5.4.1 Experiment 1: Heterogeneous preferences or budgets

In this experiment, agent heterogeneity is introduced by introducing a standard deviation of either preference or budget but keeping the mean values constant (see table 5-3). Table 5-4 compares the average and standard deviation values of six metrics between homogeneous and heterogeneous agents across four market levels. It also reports the significance level of the Wilcoxon Signed-Rank Test, which tests whether the measures between heterogeneous agents and homogeneous agents differ under each different market level. Figure 5-1 compares the spatial development and transaction price between homogenous and heterogeneous agents.

Table 5-4 Experiment 1: agent heterogeneity parameters and output metrics (average values across 40 repeated runs, standard deviations are reported in brackets) under four market levels

Level	SDP	SDB	MTC	TDP	ED	MU	MTP	Theil
L0	0	0	10.39 ^{n/a} (0.06)	400 ^{n/a} (0)	2.62 ^{n/a} (0.06)	0.84 ^{n/a} (0.00)	98.88 ^{n/a} (0.06)	N/A
	0.3	0	9.52 ^{***} (0.13)	400 ^{n/a} (0)	2.19 ^{***} (0.08)	0.87 ^{***} (0.00)	101.94 ^{***} (0.10)	N/A
	0	30	10.39 (0.06)	400 ^{n/a} (0)	2.62 (0.06)	0.84 (0.00)	98.66 (1.19)	0.02 ^{***} (0.00)
L0.5	0	0	10.39 ^{n/a} (0.05)	400 ^{n/a} (0)	2.63 ^{n/a} (0.06)	0.84 ^{n/a} (0.00)	98.87 ^{n/a} (0.05)	N/A
	0.3	0	10.13 ^{***} (0.22)	400 ^{n/a} (0)	2.46 ^{***} (0.10)	0.86 ^{***} (0.00)	100.93 ^{***} (0.16)	N/A
	0	30	10.39 (0.05)	400 ^{n/a} (0)	2.63 (0.06)	0.84 ^{***} (0.00)	99.40 ^{***} (1.20)	0.02 ^{***} (0.00)
L1	0	0	6.75 ^{n/a} (0.05)	160 ^{n/a} (2)	2.71 ^{n/a} (0.07)	0.89 ^{n/a} (0.00)	105.07 ^{n/a} (0.10)	N/A
	0.3	0	8.14 ^{***} (0.15)	281 ^{***} (5)	2.22 ^{***} (0.08)	0.89 ^{***} (0.00)	104.65 ^{***} (0.10)	N/A
	0	30	8.61 ^{***} (0.15)	238 ^{***} (9)	2.90 ^{***} (0.08)	0.87 ^{***} (0.00)	115.32 ^{***} (0.90)	0.01 ^{***} (0.00)
L2	0	0	6.76 ^{n/a} (0.04)	161 ^{n/a} (2)	2.71 ^{n/a} (0.06)	0.89 ^{n/a} (0.00)	105.04 ^{n/a} (0.12)	N/A
	0.3	0	7.50 ^{***} (0.11)	233 ^{***} (4)	2.28 ^{***} (0.08)	0.90 ^{***} (0.00)	105.34 ^{***} (0.09)	N/A
	0	30	8.61 ^{***} (0.46)	252 ^{***} (19)	2.75 ^{**} (0.06)	0.87 ^{***} (0.00)	114.31 ^{***} (1.86)	0.01 ^{***} (0.00)

SDP: standard deviation of preference for city center proximity; SDB: standard deviation of budget; MTC: mean transport cost; TDP: total developed parcels; ED: edge density; MU: mean utility; MTP: mean transaction price; Theil: Theil index based on budget distribution

* significant at 0.1 ** 0.01, and *** 0.001 with Wilcoxon Signed-Rank Test and a null hypothesis that metrics have the same distribution between scenario with heterogeneous agents and scenario with homogeneous agent under each market level. (n/a: cannot compute with ties; N/A: Theil index cannot be computed when buyers' budgets are homogeneous

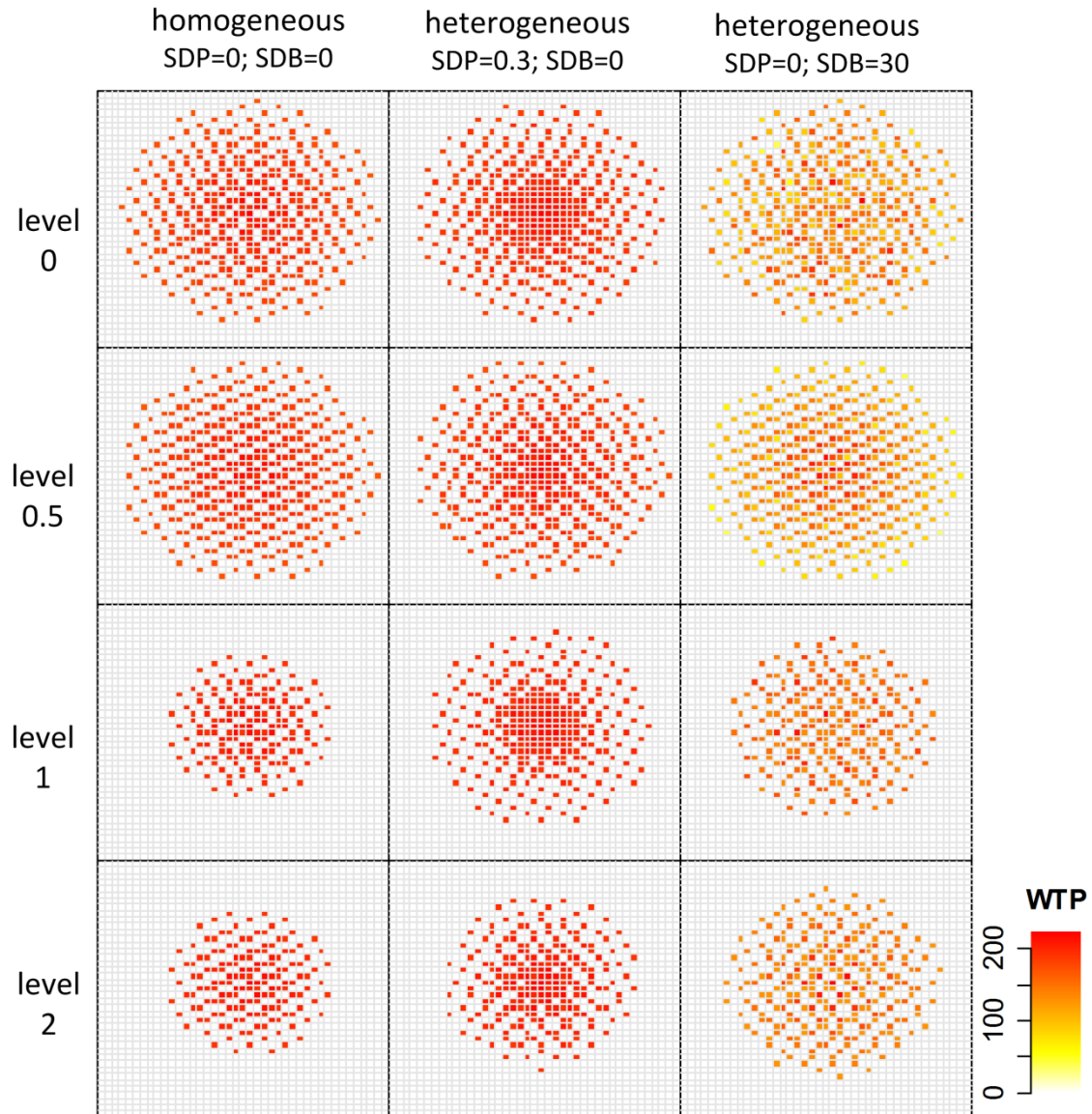


Figure 5-1 Experiment 1: land use change and transaction prices between scenario with homogeneous agents and scenario with heterogeneous agents across four market levels (all these snapshots are from the first of 40 repeated runs, SDP: standard deviation of preference for city center proximity, SDB: standard deviation of budget).

First, consistent with existing findings (Brown & Robinson, 2006; Filatova et al., 2009b; Ligmann-Zielinska, 2009; Zellner et al., 2010), most of measures show significantly different patterns between homogeneous and heterogeneous agents (Table 5-

4). The difference is also evident in spatial visualizations (Figure 5-1). More importantly, the results illustrate that heterogeneity in budget and preference plays very different roles in affecting the spatial and socioeconomic patterns. In contrast to the homogeneous case (the first column of snapshots in Figure 5-1), preference heterogeneity leads to more compact development in the urban center (the second column in Figure 5-1) because it introduces buyers who prefer to settle down in a densely developed neighborhood in the urban center. Hence, the edge density is lower compared to the homogenous cases. Meanwhile, mean utility, the measure of buyer's satisfaction, increases in L0, L0.5 and L2, because buyers with preference for either urban city or open space amenity can more easily find a parcel that gives them highest utility. Consequentially, the average transaction price increases because the WTP is highly related to the utility level (see equation 2).

Intuitively, the most prominent effect of budget heterogeneity is seen in the spatial heterogeneity of transaction prices. It is obvious that the differences in the distribution of developments are less apparent than the differences in the transaction prices between homogeneous agents (the first column in Figure 5-1) and heterogeneous agents (the last column in Figure 5-1). This conclusion is supported by the quantitative analysis. It is evident in Table 5-4 that the mean transaction prices with heterogeneous budgets are 1%-10% higher than in homogeneous budget case for market levels L0.5 - L2. However, the difference is not statistically significant in L0 because the occupation of lands in this level follows a random first-come first-serve order. The difference resulting from either preference heterogeneity or budget heterogeneity confirms that agent heterogeneity is an important factor influencing the spatial and socioeconomic outcomes. Furthermore, the results imply that preference heterogeneity is more relevant to spatial patterns, while budget heterogeneity affects the socioeconomic patterns.

Second, market mechanisms work as an important force affecting the spatial and

socioeconomic patterns. New patterns emerge between cases with homogeneous and heterogeneous agents under different market levels. For example, when budget constraints are incorporated, the mean transport cost, which indicates the range of development, reveals different results. In L0 and L0.5 (without budget constraints), the mean transport cost is 10.39 for homogeneous agents. It decreases to 9.52 (8%) and 10.13 (3%) when buyers have heterogeneous preferences in L0 and L0.5 respectively (Table 5-4). That is because the compact development driven by preference heterogeneity accommodates more agents in the urban center. However, the condition is reversed in L1 and L2 (with budget constraints). Either preference heterogeneity or budget heterogeneity would result in a more dispersed development in the suburbs (Figure 5-1). That is because the preference heterogeneity will introduce more buyers with higher preference for open space amenities who will have higher utility in the suburbs and can offer higher WTPs, and therefore can buy parcels in the suburbs. Meanwhile, budget heterogeneity will also introduce some affluent buyers with higher budgets, and their WTP will offset the transport cost. Hence, more buyers can find a location farther from the city center than the homogeneous case. In summary, budget or preference heterogeneity will induce sprawling development in the suburbs when budget constraints are incorporated, meanwhile preference heterogeneity will encourage a more compact development in the city center.

More importantly, the differences in representing the constraints and driving forces (e.g., market mechanism) can shed light on conflicting conclusions drawn by different models. As discussed in the review, using SOME, Zellner et al. (2010) found the introduction of preference heterogeneity can lead to a more compact development when the mean preference for open space amenity is high. However, Ligmann-Zielinska (2009) found that variations in risk attitudes result in a slightly less compact development. With regard to the land market elements, the difference between these two models is the latter

one has the component of competitive bidding among developers. As shown in Table 5-1, the SOME model has neither budget constraints nor competitive bidding. The compact development drawn by the SOME model is corroborated by our model; the spatial distribution in the city center is more compact in L0 when preference heterogeneity is introduced (the first two snapshots in the first row of Figure 5-1). However, the clustered city core resulting from agent heterogeneity is much smaller when competitive bidding is incorporated (the first two snapshots in the second column of Figure 5-1). The result is similar to the conclusion drawn by Ligmann-Zielinska (2009) that the risk attitude heterogeneity only leads to a less clustered development. The reason is that competitive bidding, which is also represented in the Ligmann-Zielinska's model, enhances the challenge to successfully obtain a parcel even though preference heterogeneity gives agents opportunities to settle at the urban core as long as they outbid the others.

Third, our results show there is a tendency that, as the market representation becomes more complex, the results become more different between homogeneous agents and heterogeneous agents. With an increase of market level, more market representations are incorporated in the model; and the differences of metrics between homogeneous agents and heterogeneous agents become more statistically significant (Table 5-4). For instance, in L0, the differences of all the metrics between homogeneous budgets and heterogeneous budgets are not significant, but almost all of the metrics become significantly different in L2. This tendency suggests that outcomes are more sensitive to agent heterogeneity when the model becomes more complex and similar to real world. In other words, accurately representing agent heterogeneity is an important factor to make sure the model outcomes can reliably replicate empirical processes and conditions.

5.4.2 Experiment 2: Magnitude of agent heterogeneity

To evaluate the *impacts of variation of agent heterogeneity on the outcomes*, the second experiment sequentially increases the magnitudes of heterogeneity in budget and preference respectively (Table 5-3).

Figure 5-2 and 5-4 compare the spatial pattern of development and transaction prices that resulted from different degrees of heterogeneity in budget and preferences respectively across four market levels. Intuitively, the increasing degree of budget heterogeneity will lead to a greater heterogeneity of transaction prices spatially. By contrast, the increasing degree of budget heterogeneity has relatively limited influences on the spatial pattern of development. Figure 5-3 compares the six metrics by increasing the degree of budget heterogeneity across four market levels. Metrics related to the spatial distribution of transaction prices, like mean transaction price and the Theil index, show monotonically increasing trends with the increasing degree of budget heterogeneity. In comparison, landscape metrics (mean transport cost and edge density) do not have a monotonic relationship with the increasing degree of budget heterogeneity. The nonlinearity can be, at least partially, explained by the differences in the representation of market process. For example, when the budget constraint is introduced, the total developed parcels will vary with the increasing degree of budget heterogeneity (the second row in Figure 5-3). Therefore, mean transport cost and edge density are not directly comparable with the increasing degree of budget heterogeneity and may show some nonlinear patterns (the first and third rows in Figure 5-3)

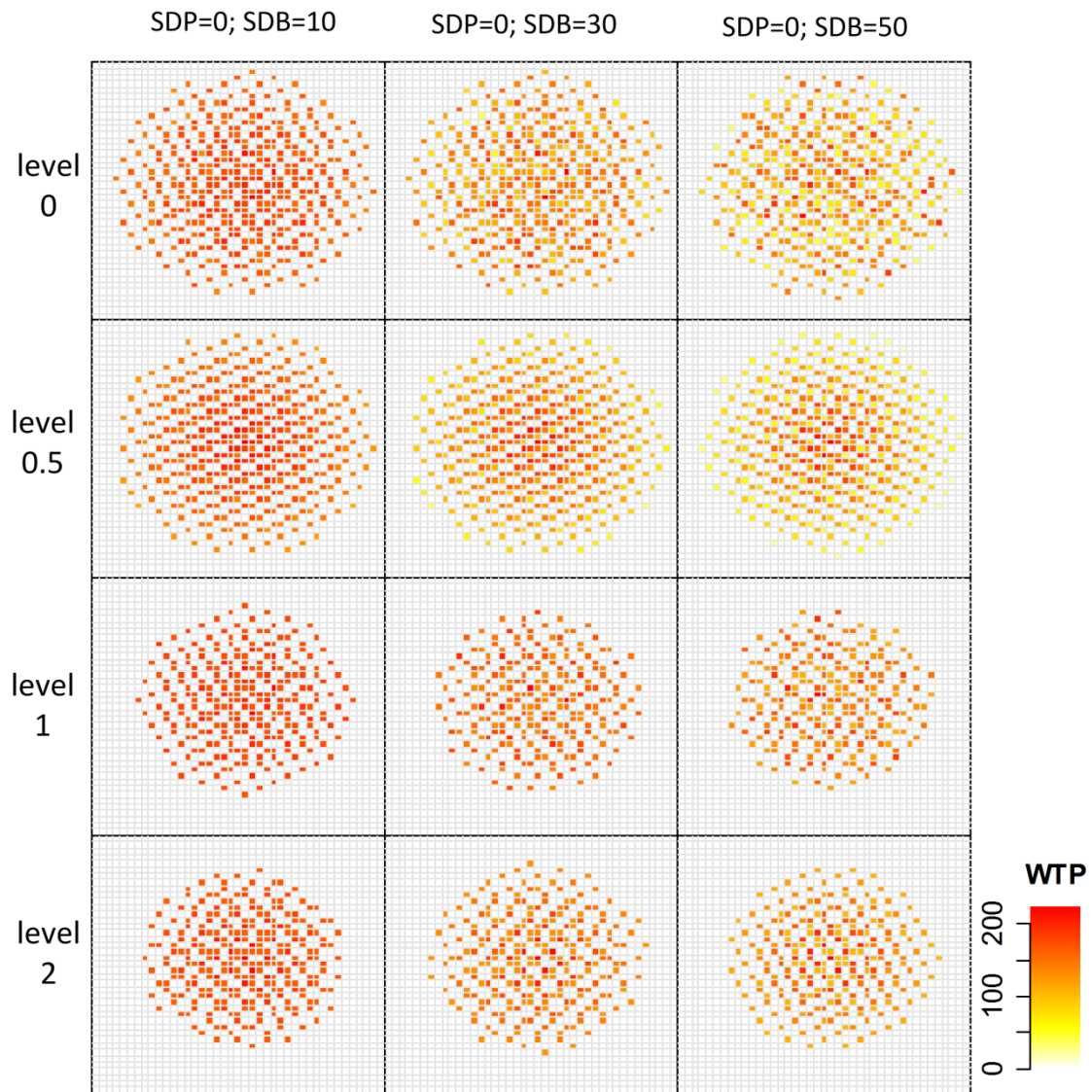


Figure 5-2 Experiment 2: land use change and transaction prices with increasing degree of budget heterogeneity across four market levels (all these snapshots are from the first of 40 repeated runs, SDB: standard deviation of budget).

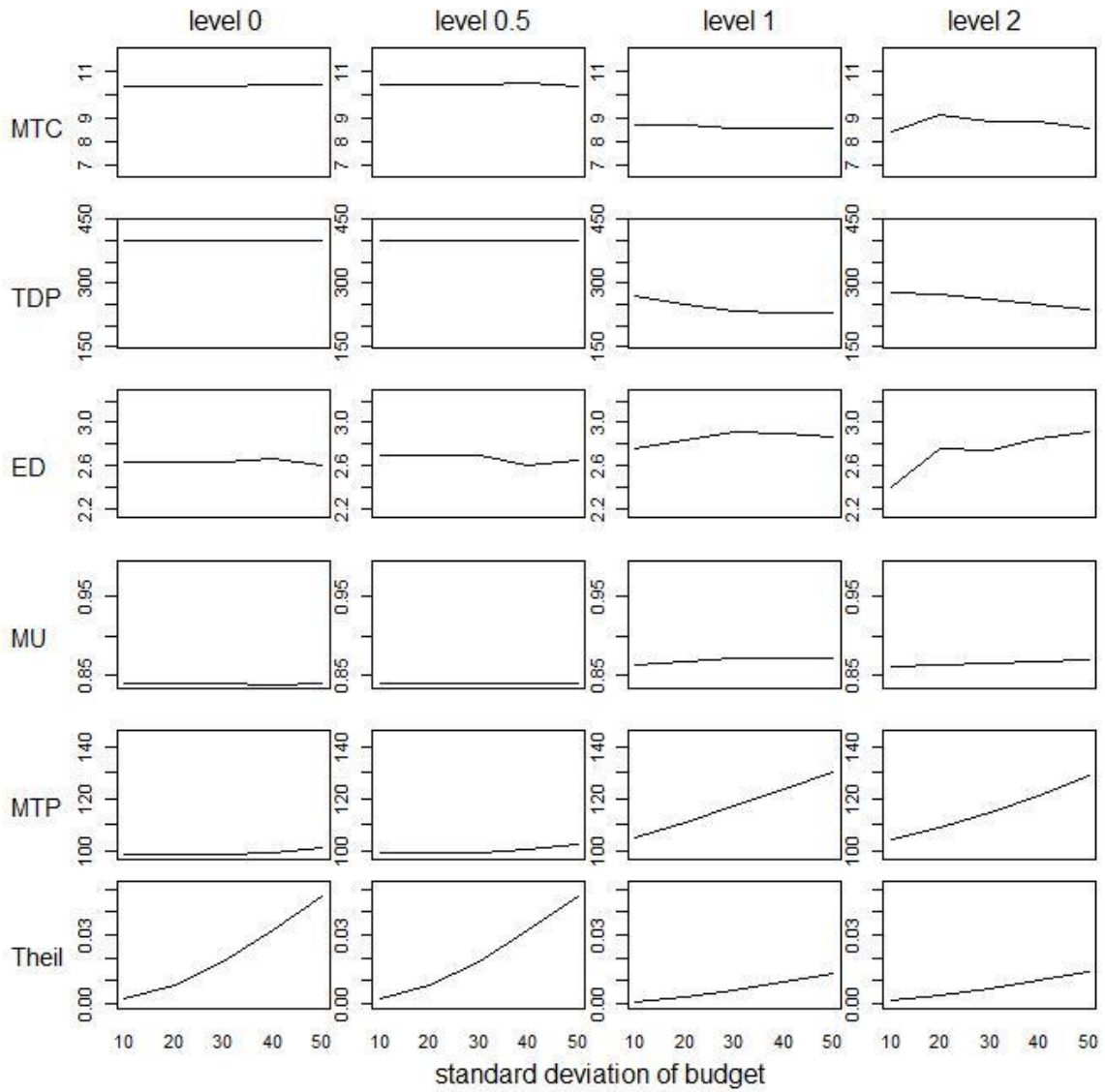


Figure 5-3 Experiment 2: comparison of metrics with increasing degree of budget heterogeneity across four market level (average value across 40 repeated runs, MTC: mean transport cost; TDP: total developed parcels; ED: edge density; MU: mean utility; MTP: mean transaction price; Theil: Theil index based on budget spatial distribution).

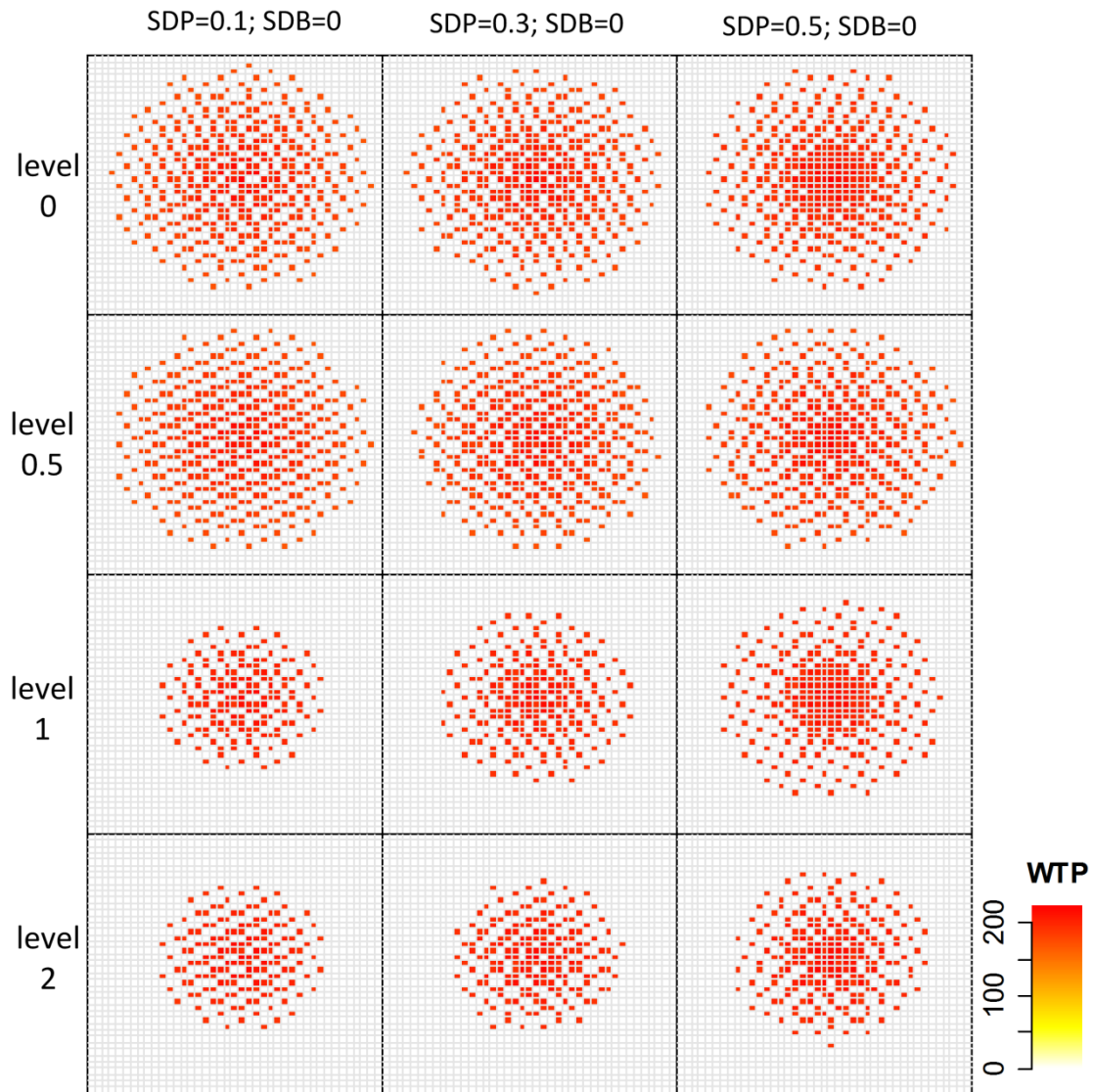


Figure 5-4 Experiment 2: land use change and transaction prices with increasing degree of preference heterogeneity across four market levels (all these snapshots are from the first of 40 repeated runs, SDP: standard deviation of preference for city center proximity).

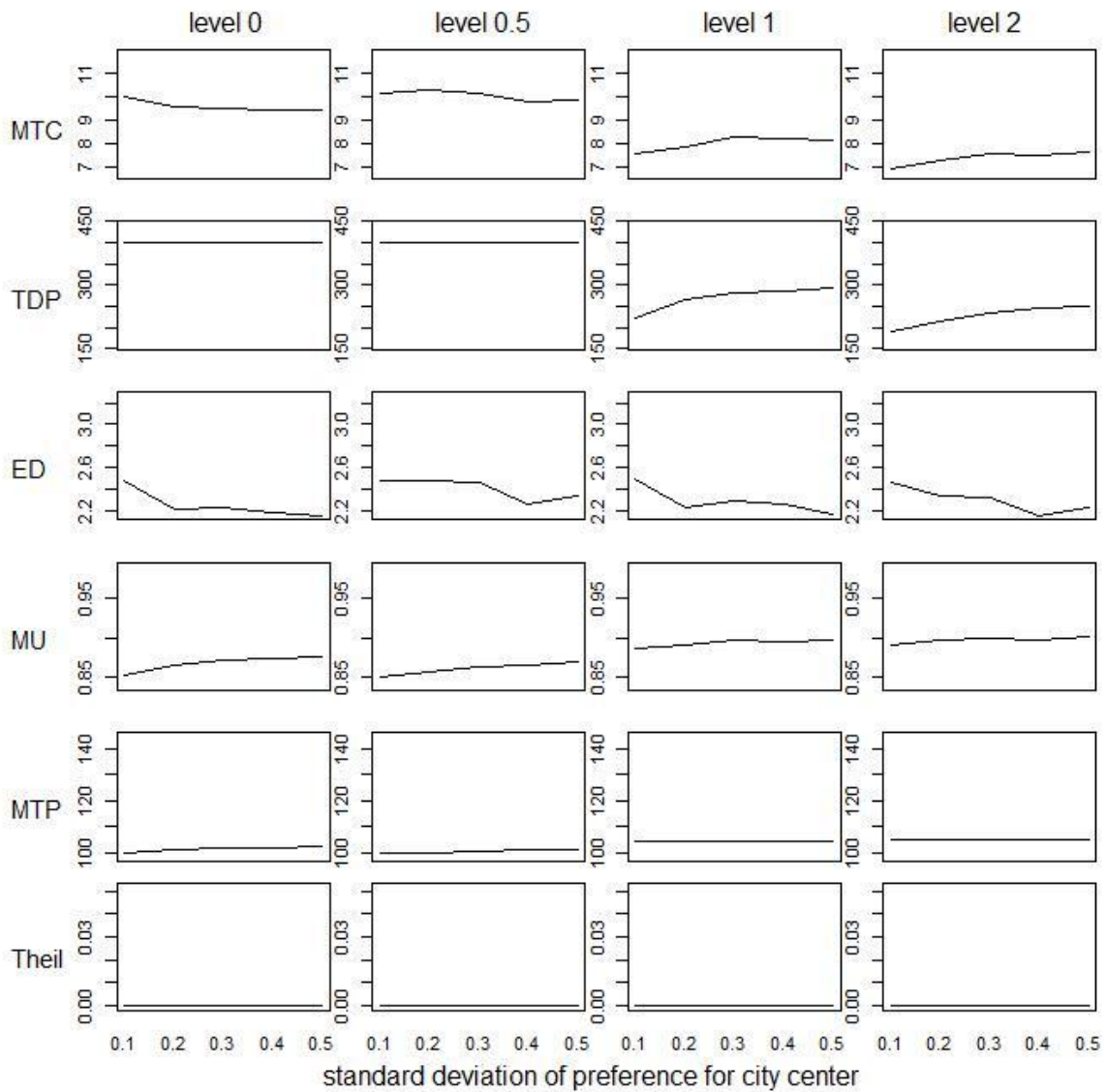


Figure 5-5 Experiment 2: comparison of metrics with increasing degree of preference heterogeneity across four market levels (average value across 40 repeated runs, MTC: mean transport cost; TDP: total developed parcels; ED: edge density; MU: mean utility; MTP: mean transaction price; Theil: Theil index based on budget spatial distribution).

For preference heterogeneity, the situation is reversed. Landscape metrics are more sensitive to an increasing degree of preference heterogeneity. From Figure 5-4, it is clear that the increasing degree of preference for proximity to CBD will encourage compact development in the urban core. Thus, edge density decreases with the increasing

degree of preference heterogeneity across four market levels. Total developed parcels is constant for L0 and level L0.5 since no budget constraint exists, and all the buyers can find a land. Meanwhile, the mean transport cost decreases with the increasing degree of preference heterogeneity in these two levels because the spatial development becomes more compact. However, total developed parcels increases with the increasing degree of preference heterogeneity in L1 and L2 (Figure 5-5) because, for a given budget, buyers with heterogeneous preferences are more likely to find a parcel they can afford. Some of these increased developments locate in the suburbs and therefore enhance the sprawling development. The increase in mean transport cost with the increasing degree of preference heterogeneity in L1 and L2 confirms this phenomenon (Figure 5-5). In summary, the increasing degree of preference heterogeneity induces more compact developments in the city center but more sprawling developments in the suburbs (Figure 5-4). In addition, the non-monotonic relationship between landscape metrics (i.e. edge density and mean transport cost) and the increasing degree of preference heterogeneity is more apparent. That is because the compact development in the city center and the sprawling development in the suburbs, which simultaneously results from the increasing degree of preference heterogeneity, will counteract the effects of each other in calculating landscape metrics.

The results corroborate the findings from previous section: preference heterogeneity affects the spatial patterns of development (e.g., compactness of development, range of developments) but budget heterogeneity has greater impacts on individual transaction prices and the spatial distribution of transaction price. Furthermore, unlike the previous work based on the SOME model, which concludes heterogeneity in agent leads to a sprawling development regardless of the degree of heterogeneity (Brown & Robinson, 2006), the results with competitive bidding and budget constraints show a more complicated pattern of development. The introduction of agent heterogeneity can

result in compact developments in the city center and sprawling developments in the suburbs simultaneously. The relationship between metric and the increasing degree of heterogeneity is not uniformly monotonic.

5.4.3 Experiment 3: Interactions of agent heterogeneity in multiple dimensions

To understand how *the collective effects from multiple sources of agent heterogeneity vary under different market representations*, the last experiment changes the standard deviation of both preference and budget simultaneously. Figure 5-6 and 5-7 compare the six metrics in a 3D surface with the increasing degree of both preference heterogeneity and budget heterogeneity. As discussed in the previous part, the impacts of increasing degree of agent heterogeneity could be either monotonic or non-monotonic. Hence, the collective effects from the two sources of agent heterogeneity are more complex. Generally, there are three kinds of collective effects.

First, one type of agent heterogeneity plays the dominant role in affecting the trends. For example, mean utility gradually increases with an increasing degree of preference heterogeneity across four market levels, but remains stable regardless of the increasing degree of budget heterogeneity (see the first column in Figure 5-7). That is because the increasing degree of budget heterogeneity has relatively limited effects on mean utility, while the dominant influence comes from preference heterogeneity. A contrary example revealing the dominant influence of budget heterogeneity can be found in the results of Theil index (last column in Figure 5-7). Obviously, increasing degree of budget heterogeneity has monotonically positive effects on Theil index across the four market levels. The increasing degree of budget heterogeneity will increase the range of transaction price and therefore intensify the wealth inequality under each market level.

Since the Theil index measures the evenness of budget, it will not vary when the budget is fixed.

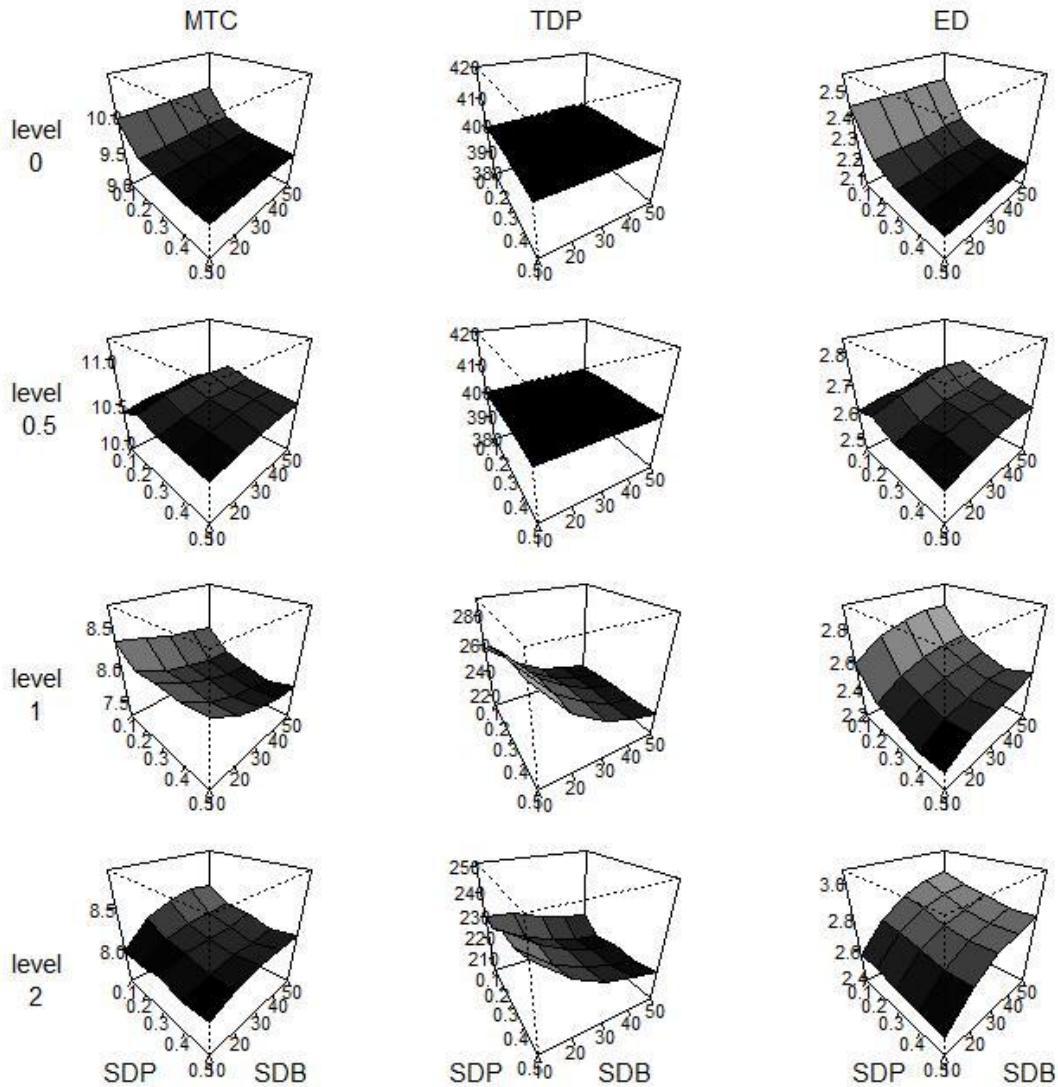


Figure 5-6 Experiment 3: comparison of landscape metrics with simultaneously increasing degrees of preference heterogeneity and budget heterogeneity across four market levels. The horizontal axes represent SDP (standard deviation of preference for city center proximity) and SDB (standard deviation of budget) respectively. A lighter color indicates a higher value (average value across 40 repeated runs, MTC: mean transport cost; TDP: total developed parcels; ED: edge density).

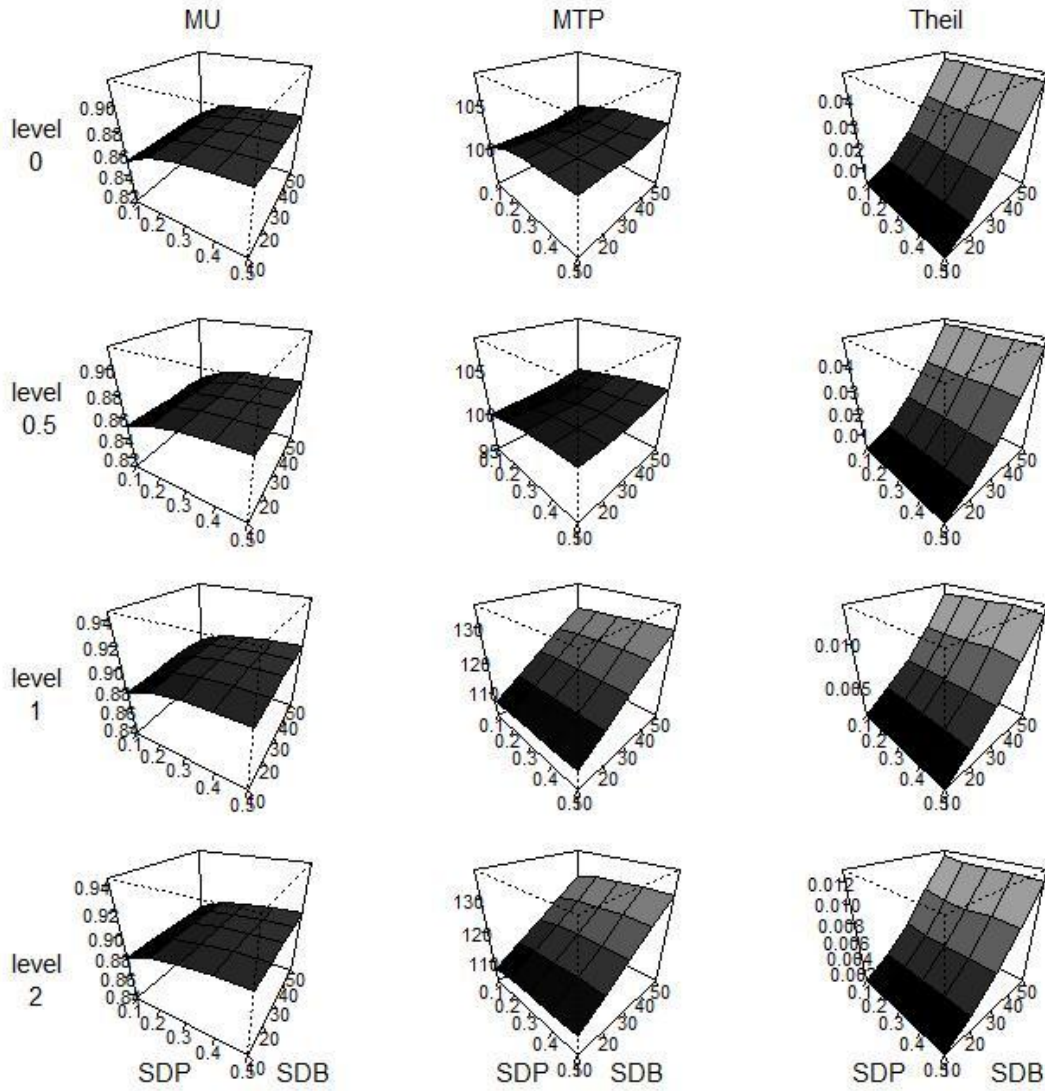


Figure 5-7 Experiment 3: comparison of socioeconomic metrics with simultaneously increasing degrees of preference heterogeneity and budget heterogeneity across four market levels. The horizontal axes represent SDP (standard deviation of preference for city center proximity) and SDB (standard deviation of budget) respectively. A lighter color indicates a higher value (average value across 40 repeated runs, MU: mean utility; MTP: mean transaction price; Theil: Theil index based on budget spatial distribution).

Second, the metrics are relatively independent to the increasing degrees of both budget heterogeneity and preference heterogeneity. For instance, the total number of developed parcels is constant in L0 and L0.5 (the second column in Figure 5-6) and mean transaction price remains relatively stable in L0 and L0.5 (the second column in Figure 5-7). That is because, in L0 and L0.5, all the buyers can finally find a place to live, and the mean budget, which strongly relates to the transaction price, remains constant even though its standard deviation increases. In other words, the market representation is the vital force in determining the independent relationships with increasing degree of agent heterogeneity for these metrics.

Third, budget heterogeneity and preference heterogeneity have opposite effects on some metrics, and the combined effects are not monotonic. This phenomenon can be found in the variations of edge density across market levels (the last column in Figure 5-6). In L0, the increasing degree of preference heterogeneity results in a monotonically more compact development. However, the influence from variations of budget heterogeneity is negligible (the first snapshot in the last column of Figure 5-6), because buyers with higher preferences for urban centers are more likely to find a parcel in the center. When the competitive bidding is introduced in L0.5, the monotonic trend is interrupted. A relatively small variation of preference heterogeneity (i.e. SDP (standard deviation of preference) = 0.1) in L0.5 will not lead to a more sprawling development than a larger variation of preference heterogeneity (i.e. SDP = 0.2) as in L0 (the second snapshot in the last column of Figure 5-6). That is because when the variation of preference heterogeneity is relatively small, the number of buyers getting parcels in the city center through competitive bidding is almost the same, but a relatively larger SDP (i.e. SDP = 0.2) allows for more buyers who cannot tolerate high residential density in the city center. Thus, the sprawling development is more prominent when SDP equals to 0.2 than 0.1. However, when SDP becomes even larger (SDP > 0.3), buyers with higher tolerance for crowded development will lead to more infill developments. When budget constraints are included in L1, the monotonic effect on inducing the sprawling development caused by an increasing degree of budget heterogeneity becomes more prominent (the third snapshot in the last column of Figure 5-6), because budget constraints allow more affluent buyers who prefer open space amenities to find parcels

far from the city center. At L2, the trend is reversed from L0: the effect on edge density resulting from the increasing degree of budget heterogeneity will surpass the influence caused by the increasing degree of preference heterogeneity, and become more evident (the last snapshot in the last column of Figure 5-6). The reason is that competitive bidding and budget constraints greatly enhance the possibility that buyers with higher budget and higher preference for open space amenities choose parcels in the suburban area. In the meantime, the buyers who may encourage infill developments, including buyers with lower budget and higher preference for open space amenities, or buyers with lower budget and lower preference for amenities, are more likely to fail in the process of bidding or offering a WTP larger than agricultural opportunity costs. Hence, the development becomes more fragmented.

Such findings demonstrate that the collective effects of the two sources of agent heterogeneity are complex. The results depend on the market representation and metric sensitivity to each source of agent heterogeneity. In other words, increasing degree of one type of agent heterogeneity is likely to counteract the effect of increasing variations of another type of agent heterogeneity. The result is also consistent with the conclusion drawn by Ligmann-Zielinska (2009). She found when there are multiple developers with different combinations of heterogeneous risk attitudes, their collective effects on spatial patterns are negligible. Due to the counteracting effects from different combinations of heterogeneity, the difference in the result is indiscernible.

5.5 Conclusion and Discussion

This chapter evaluates the effects of agent heterogeneity in an agent-based land market model. Three series of experiments are designed to explore how the introduction of agent heterogeneity, degree of agent heterogeneity and collective effect of multiple sources of agent heterogeneity affect the model outcomes, in both spatial and socioeconomic dimensions. The results demonstrate that agent heterogeneity has considerable impacts on the spatial distribution of land use as well as socioeconomic outcomes. More specifically, we found the landscape metrics and socioeconomic outcomes between homogeneous

agents and heterogeneous agents are significantly different, especially when more market mechanisms are incorporated. These results indicate the complex interactions between agent heterogeneity and market representation and the importance of agent heterogeneity in an ABLMM. In terms of the effects of agent heterogeneity, the two sources of agent heterogeneity examined in our experiments have different effects. Budget heterogeneity induces changes in transaction price and spatial fragmentation, and the increasing degree of budget heterogeneity will lead to a more heterogeneous distribution of transaction price. Preference heterogeneity, by contrast, is highly pertinent to spatial patterns, and the increasing degree of preference heterogeneity will encourage compact developments in the urban core but sprawling developments in the suburbs.

These findings imply that the relationships between agent heterogeneity and macro measures are not uniformly monotonic. They indicate the importance of introducing an appropriate magnitude of agent heterogeneity in an empirical study. Our findings also suggest that differences in market representation are likely to be an important factor in reconciling some conflicting conclusions drawn by some other models. With regard to the collective effects from multiple sources of agent heterogeneity, our results show the difference among metrics depends on both the market representations and the interactions of agent heterogeneity. Further, the effects of the two sources of agent heterogeneity can counteract each other, which can potentially lead to some emerging results. It also suggests the ability of ABM to simulate emergent phenomena at the aggregated level from agent heterogeneity at the individual level.

One interesting and unanticipated point to emphasize is that the limitations of the models with less market representation are revealed only in the cases of heterogeneous agents. Taking a closer look at the results at market L0, the homogenous case shows a classic downward-sloping rent gradient as in the classic models of Von Thünen and Alonso. It, however, disappears with heterogeneous agents (see first row of 3D bar charts in Figure 5-8). Yet, in markets L0.5 and L2, in which competitive bidding is activated, the rent gradients and circular zones of land prices ranges appear again with and without budget constraints (see the second and the fourth rows in Figure 5-8). It implies that competitive bidding is essential to reproduce the result of classical urban land market models in a spatial ABM, especially if agents are heterogeneous.

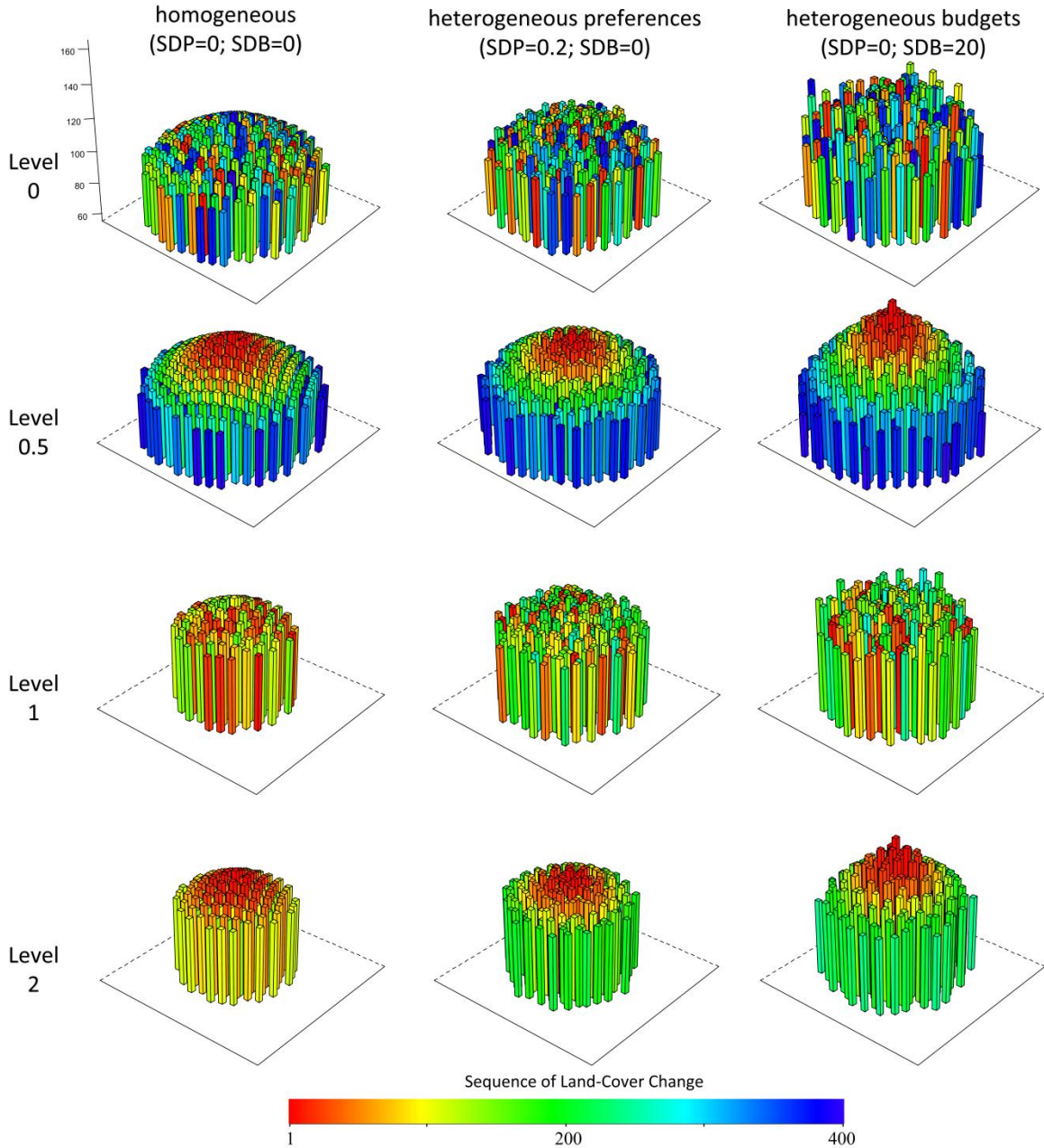


Figure 5-8 Effects of market levels and agent heterogeneity on the spatial outcomes of rent gradients and sequence of land-use changes (all these 3D bar plots are from the first of 40 repeated runs. The vertical bars represent the transaction prices. SDP: standard deviation of preference for city center proximity, SDB: standard deviation of budget)

LUXE provides the opportunity to evaluate complex interactions in a land market due to its capability to encapsulate multiple sources of agent heterogeneity as well as its potential to offer broader kinds of outputs. To our knowledge, this is one of the first

attempts to systematically explore the effects of agent heterogeneity in an ABLMM. Both landscape patterns and socioeconomic patterns are evaluated by different measures. The results enrich our understanding on the processes that drive residential pattern, and give us more confidence in confirming the importance of agent heterogeneity and market representations.

There are also some inevitable limitations to this study. Currently, although the model simulates residential choice beyond the means of static economic equilibrium by introducing bilateral interactions between agents, the dynamics of immigration and emigration are not included. Additionally, the model is a relatively closed system since all the buyers are introduced into the model at initialization. Simulating the timing of buyers entering the model based on empirical data is a challenge that we aim to address in the future. Similarly, the buyers are not allowed to relocate once they settle. The relocation process, such as affluent households moving to suburb due to the local neighborhood degradation, cannot be simulated in the current version. However, studies shows the relocation process is also one of the main factors in shaping the urban landscape (Benenson, 1998; Dieleman, 2001; Ettema, 2011). Hence, simulating the relocation process is the next step to improve the model.

Finally, only two sources of agent heterogeneity (i.e. budget and preference heterogeneity) were examined in this chapter. The rationale for choosing these two is that, intuitively, they are highly related to land market processes represented in LUXE (i.e. budget constraints and competitive bidding). However, additional sources of agent heterogeneity potentially play important roles in influencing land market outcomes, such as risk attitudes (Filatova et al., 2011a; Ligmann-Zielinska, 2009), and ability to process knowledge (i.e., bounded rationality (Manson, 2006; Manson & Evans, 2007)). LUXE has a mechanism to incorporate bounded rationality by limiting the number of parcels that a buyer evaluates for bidding, in order to simulate incomplete market information. This mechanism is switched off in the current chapter, in order to minimize random elements and provide a clean test of the effects of land markets and comparison to the benchmark analytical urban land market model. The next stage of model development will also incorporate risk attitudes and uncertainty.

Chapter 6 Conclusions and Discussions

6.1 General conclusion and contribution

In this thesis, three major tasks – spatial analysis of land-cover changes within exurban residential parcels, reviewing progresses of ABMs and exploring the effects of agent heterogeneity and land-market representation – are achieved through various methods, including calculations of landscape metrics and spatial autocorrelation indicators, literature review and synthesis, and experimental design. A distinctive feature of this dissertation is that all the three tasks focus on bottom-up analysis, namely, the land-cover change at the parcel level, the features of agent-based residential choices model whose unit of analysis is the land parcel, at the level of model component, and the effects of agent heterogeneity and land market representation at the agent level. General answers to the 6 research question given in Chapter 1 and the contributions of each chapter are given below:

Q1: How are land-cover composition and configuration altered at the parcel level during the period from 1960 to 2000 in the exurban areas of Southeastern Michigan?

The results in Chapter 3 show that the number and areas of exurban residential parcels increased steadily in the three townships from 1960s and 2000s. The results related to the temporal distribution of parcels groups by nine levels of parcel size reveal that the number of parcels with a size close to 1 acre showed the most prominent growth, while parcels with a size larger than 6 acres have the slowest growth rate in numbers. In addition, the quantity and pattern of land cover vary substantially among the four main land-cover types (i.e. tree cover, impervious structure, maintained lawn and open fields). Areas of tree cover increased and showed a more fragmented distribution and irregular shape over time. Most parcels have only one patch of impervious structure, and the acreage and fragmentation of impervious structures remained relatively stable over time. On average, maintained lawn has the largest total land cover relative to the other three

land-cover types. The values of landscape metrics for open fields are less regular and have larger standard deviations than the other land-cover types. This is because open fields have a broad definition of land covers, and mainly large-size parcels have open fields.

Q2: Is the land-cover pattern of individual parcels consistent with the neighborhood appearance over time? Is it possible to identify representative parcels that have experienced a convergence process, in which land-cover quantities and/or patterns in exurban residential parcels conform the neighborhood appearance?

The results in Chapter 3 show that the similarities of most landscape metrics (except edge density) in the neighborhood for the three major land-cover types (i.e. tree cover, impervious structure and maintained lawn) increased over time with some small fluctuations. This implies that the land-cover patterns have a convergent trend in the neighborhood. The results also show that the increase in spatial similarity is related to multiple factors, e.g., the number of parcels, the dominant parcel size, and the characteristics of patterns for each land cover.

To our knowledge, Chapter 3 is the first report on the temporal change of land-cover patterns within exurban residential parcels. The results have the potential to disentangle the linkage between land-cover change and ecosystem services in the coupled human-environment system in exurban areas. Specifically, they provide a stepping stone to understanding the drivers of land-cover change within exurban residential parcels, and to accurately measuring consequent change of ecosystem services.

Q3: How do existing applications of ABMs fill in the continuum that runs from purely theoretical to extensively empirical models?

Chapter 4 reviews 51 agent-based urban residential models. Generally, they can be divided into three categories: classical models extended using ABM, models simulating different stages of urbanization process, and integrated ABM and microsimulation models. Their features are summarized and compared within each category in detail in Chapter 4.

Q4: What are the differences among existing ABMs that simulating urban residential choices in handling agent heterogeneity, land market components and output measurement?

According to the review in Chapter 4, agent heterogeneity is introduced into a model by changing either agents' attributes or their decision-making rules. Although most models have agent heterogeneity, the methods of evaluating the effects of agent heterogeneity on the outcomes of urban dynamics/patterns are insufficient. Four land market elements – preferences, resource constraints, competitive bidding, and endogenous relocation – are compared in Chapter 4. Among them, preferences are the most commonly represented element, while competitive bidding is the least. Resource constraints and endogenous relocation are less popular than preferences, and the implementation of endogenous relocation usually does not represent the direct interactions between households and the land market. With regard to output measurement, the review found that ABMs can provide a broader range of outputs than traditional techniques of modeling (e.g., statistical models, system dynamic models and cellular automata models). It is necessary to use a wide range of methods and metrics (including individual level observations), to verify and validate models, and to analyze and visualize outputs.

To our knowledge, Chapter 4 is the first and most comprehensive report reviewing the progresses in simulating urban residential choices using agent-based modeling. The review plays various roles for a broad dimension of readers. For a beginner to ABM, it provides an indexing guide on the progress and common features of residential choice models based on ABM. For senior researchers, it provides an opportunity to place their models in the context of other related work and to potentially improve their models by considering a broader representation of agent heterogeneity, land markets, and output measurement. For researchers in related disciplines, it provides an interface to link their methods to improve model development (i.e., machine learning, graph theory), and leverage findings in other disciplines (i.e., drivers of land-cover, land-use, and land-management change in social and economic studies) to empirically parameterize their models.

Q5: How does agents' heterogeneity in incomes and in locational preferences theoretically affect emerging land-use patterns? How does the degree of heterogeneity in the agents' population affect spatial and economic phenomena? And do the collective effects from multiple sources of agent heterogeneity vary under different market representations?

Chapter 5 evaluates the effects of agent heterogeneity and land market representation in a stylized ABM (LUXE) by three series of experiments. The results demonstrate that agent heterogeneity has considerable effects on the spatial distribution of land-use change as well as socioeconomic dynamics. The two sources of agent heterogeneity have different impacts. Specifically, budget heterogeneity induces changes in the spatial distribution of transaction prices and spatial fragmentation. In contrast, preference heterogeneity is highly pertinent to spatial patterns and encourages a pattern of developments with compact developments in the urban core and sprawling developments in the suburbs.

Q6: Do the outcomes of the theoretical monocentric city differ in different representations of market elements, especially in the existence of agent heterogeneity? Are different representations of market elements able to reconcile some conflicting results about the effects of agent heterogeneity drawn by other models?

The result in Chapter 5 shows that the classic downward-sloping rent gradient from the urban center in classical models of Von Thünen/Alonso cannot be produced when agents are heterogeneous and the land market element of competitive bidding is missing. In other words, it implies that competitive bidding is essential to reproduce the result of classical urban land market models in a spatial ABM, especially if agents are heterogeneous. In addition, the results suggest that differences in market representation are likely to be an important factor in reconciling some conflicting conclusions drawn by some other models. That is because the relationship between model outcomes and agent heterogeneity is not uniformly monotonic, and the effects of the two sources of agent heterogeneity can counteract each other, which can potentially lead to some nonlinear and emergent results.

To our knowledge, Chapter 5 is the first report comprehensively evaluating the

effects of agent heterogeneity in a stylized agent based land market model. It takes a step back to explore the rationale and challenges for adding more components (agent heterogeneity and land market representation in this case) in agent-based LUCC models.

6.2 Challenges and future work

This thesis offers a step further to examine exurban LUCC by integrating the methods of measurement, review and modeling. The implications and limitations for each study are discussed in length in corresponding chapters (Chapter 3-5). This section offers a discussion of the general challenges and potential solutions to them inherent in such research. In addition, this thesis only examined two challenges of exurban LUCC (i.e., spatial analysis of monitoring/observation data and modeling) addressed by Turner et al. (2007), and a number of future studies are recommended.

6.2.1 Challenges and potential solutions

Drivers of LUCC and linkage between LUCC and ecological consequences: The exurban land system is a complex coupled human-environment system. By measuring the temporal change of land-cover patterns within residential parcels, the complexity in driving a convergence of land-cover patterns gradually unfolds. Although cultural and social norms play an important role in influencing land-cover design at the neighborhood level, other factors (e.g., natural growth of trees and grasses, a common developer, environmental awareness) can also affect land-cover patterns in the neighborhood. Survey questionnaires at community level can distinguish these drivers. Additional information about the housing prices and land-management strategies can be collected simultaneously. The SLUCE project has endeavored to collect these empirical data (e.g., Nassauer et al., 2009), and more collections are in progress. Such information can facilitate additional research on the impacts of land-cover change on housing prices and ecological consequences at parcel level. In addition, methods and findings in related disciplines, such as research on epidemiology and communication (Lloyd and May,

2001), can provide insights on how to trace the change of land-cover patterns influencing by mass media or social network from the perspective of cyberspace rather than the perspective of physical space. For example, studies on virus and information spreading among computers, people and internet (Barabási and Albert, 1999; Lawrence and Giles, 1999; Lloyd and May, 2001) can shed light on the spreading of social and cultural norms on land-cover management among netizens¹⁴.

Another improvement in existing LUCC models is to incorporate the simulation of the ecological influence of LUCC by considering the sources, paths, sinks, and affected ranges of material and energy flows. Therefore, the competition for beneficial ecosystem services and gradual reduction of detrimental ecological impacts along the path can be simulated, which can provide more accurate information for stakeholders. The SPANs (Service Path Attribution Networks) is an exemplary preliminary model (Johnson et al., 2012).

Operational challenges of data collection: in this study, a challenge I consistently confronted is a deficiency of data at the individual level. More specifically, the deficiency of data is owing to availability of data within the SLUCE group (e.g., the survey data of households' preferences for landscape design) and between the SLUCE project and other institutions (e.g., housing price data in local real estate agencies). Although surveys and interviews are traditionally methods used to retrieve information at the individual level, development of new techniques can be used as alternative sources for retrieving the information. For example, location-based services (such as Foursquare, Twitter) can provide information on individual's travel and activity pattern. The information can feed back into models to evaluate the effects of exurban travel patterns on greenhouse gas emission and noise generation (Bar-Gera, 2007). In addition, consumption habits stored in local supermarkets (e.g., point card, bonus card programs), for instance, the consumption habit of water (Allon and Sofoulis, 2006), can reveal local customers' land-management habits (i.e., frequency of fertilizer and insecticide consumption). In other words, there are potential gold mines for retrieving important information for land-use change modelers, if cost and confidentiality constraints do not stand in the way of

14. An approach to use epidemic model was also suggested to model neighborhood effects in land management by SLUCE2 team member Calvin Pritchard.

accessibility by researchers.

Output measurement and visualization: measuring and visualizing model output is a challenge in ABM because a broad range of spatial, socio-economic, and agent-level outputs can be generated simultaneously by the model. However, analyzing behaviors at the agent level can provide opportunity to understand the path dependence and emergence of complex systems. For example, tracing individual activity (e.g., land-management strategy, land-cover design, and transaction history) can potentially identify a tipping point of “phase change” (e.g., adoption of new land-management strategy and land-cover design, and land/housing market boom/collapse, see (Scheffer et al., 2012)). Visualizing model outputs serves as a vehicle to communicate model outcomes with other researchers and stakeholders. However, the broad dimension of outputs requires careful organization and presentation. For example, clearly and neatly displaying multiple three-dimensional figures is a work of science and art, which cannot be easily achieved by existing modeling platforms (e.g., Eclipse, Netlogo, Swarm). Therefore, developing improved output visualization for existing agent-based modeling platforms, and/or developing interfaces and connections with other programming language (e.g., R and Matlab) will facilitate the communication within the academic sphere and reach audiences beyond the agent-based modeling research community (e.g., planners, environmentalists, and others).

6.2.2 Future work

First, a future modeling work that can connect empirical land-cover changes with theoretical ABM is strongly suggested, which is also the focus of current SLUCE project (e.g., Robinson et al., in press). In the real-world situation, the changes from rural natural parcels to exurban residential parcels are driven by multiple factors, including agent heterogeneity, spatial heterogeneity, and institutional and historical forces. However, the stylized ABM adopted in this thesis has not accounted for all these factors. In order to replicate trajectories of LUCC in exurban area as accurately as possible, more empirical data and extensive analyses for the causes and feedbacks among agents and between agents and the environment in exurban systems need to be collected and investigated.

Similarly, a lot of work needs to be done to further disentangle the complexity of land-cover dynamics that follow land-use change in exurban areas, including complementing existing datasets with corresponding records of the characteristics of households (e.g., income, number of children, and number of cars) and houses (e.g., style, price, and footage), exploring the relationships between land-cover patterns and socio-economics at the household level, surveying residents' responses to land-use changes and the consequences of land-cover and land-use changes. In other words, the next stage of the study is to face the second challenge of LUCC study – understanding the causes and feedbacks of LUCC in the coupled human-environment system.

Second, the fourth challenge of LUCC study – assessment of consequent impacts (e.g., vulnerability, resilience, or sustainability) – will be the next step to improve current work. The results in Chapter 3 about land-cover dynamics within residential parcels will be a valuable data source that can be used to evaluate the effects of anthropogenic activities on exurban ecosystems. It provides an opportunity to estimate the ecological consequences of exurban LUCC, such as changes in carbon storage, water and air quality, natural habits and biodiversity (some of these changes may require process models rather than pattern output). The results can be compared with the conditions in rural areas with fewer anthropogenic activities or in urban areas with more compact development. Such analysis will provide a more comprehensive understanding of consequences of urbanization and guide our planning policies to reach the ultimate goal of sustainability.

Third, it is a long path to transform scientific findings to practices of land-use planning. Although this thesis integrates empirical findings of land-cover dynamics and theoretical outcomes of land-use modeling from the bottom up by combining inductive methods, which infer general principles from empirical observations, and deductive methods, which reach specific conclusions from general statements (Nolan et al., 2009), it doesn't directly provide practical directions to guide exurban development. Only by accomplishing the two major improvements mentioned above (the understanding of the causes and feedbacks and the assessment of consequences) can we obtain a more comprehensive image of urbanization processes and consequences. And only through a more comprehensive and empirical model can we project and compare different paths of development in exurban areas by various scenarios from both the scientific and practical

perspectives.

References

- Agarwal C G, Glen M.; Grove, J. Morgan; Evans, Tom P.; Schweik, Charles M., 2002, "A Review and Assessment of Land-Use Change Models: Dynamics of Space, Time, and Human Choice.", in *GTR NE-297. Newton Square, PA: U.S.D.A. Forest Service, Northeastern Research Station* p 61
- Alberti M, 2005, "The Effects of Urban Patterns on Ecosystem Function" *International Regional Science Review* **28** 168-192
- Alberti M, 2008, "Urban Patterns And Ecosystem Function", in *Advances in Urban Ecology: Integrating Humans and Ecological Processes in Urban Ecosystems* (Springer, US) pp 61-92
- Alig R J, Kline J D, Lichtenstein M, 2004, "Urbanization on the US landscape: looking ahead in the 21st century" *Landscape and Urban Planning* **69** 219-234
- Allon F, Sofoulis Z, 2006, "Everyday Water: cultures in transition" *Australian Geographer* **37** 45-55
- Alonso W, 1964 *Location and land use: toward a general theory of land rent* (Harvard University Press, Harvard)
- An L, 2012, "Modeling human decisions in coupled human and natural systems: Review of agent-based models" *Ecological Modelling* **229** 25-36
- An L, Brown D G, Nassauer J I, Low B, 2010, "Variations in development of exurban residential landscapes: timing, location, and driving forces" *Journal of Land Use Science* **6** 13-32
- Anas A, 1990, "Taste heterogeneity and urban spatial structure: The logit model and monocentric theory reconciled" *Journal of Urban Economics* **28** 318-335
- Anas A, Arnott R, Small K A, 1998, "Urban Spatial Structure" *Journal of Economic Literature* **36** 1426-1464
- Anselin L, 1995, "Local Indicators of Spatial Association—LISA" *Geographical Analysis* **27** 93-115
- Anselin L, Syabri I, Kho Y, 2006, "GeoDa: An Introduction to Spatial Data Analysis" *Geographical Analysis* **38** 5-22
- Arthur W B, 1988, "Urban system and historical path-dependence", in *Working Paper Series* (Stanford University, Stanford Institute for Population and Resource Studies, Stanford, California)
- Arthur W B, 1999, "Complexity and the economy" *Science* **284** 107-109
- Arthur W B, 2005, "Out-of-equilibrium economics and agent-based modeling", in *Handbook of Computational Economics, Vol. 2: Agent-Based Computational Economics* Eds K Judd, L Tesfatsion (ELSEVIER, North-Holland)
- Augustijn-Beckers E-W, Flacke J, Retsios B, 2011, "Simulating informal settlement

- growth in Dar es Salaam, Tanzania: An agent-based housing model" *Computers, Environment and Urban Systems* **35** 93-103
- Axelrod R, 1997 *The Complexity of Cooperation: Agent-Based Models of Competition and Collaboration* (Princeton University Press, Princeton)
- Axtell R, 2000, "Why agents? On the varied motivations for agent computing in the social sciences", in *Working Paper 17, Center on Social and Economic Dynamics, Brookings Institution*
- Axtell R, 2003, "The new coevolution of information science and social science: from software agents to artificial societies and back or how more computing became different computing", (Brookings Institution)
- Ban H, Ahlqvist O, 2007, "Visualizing the Uncertainty of Urban Ontology Terms Ontologies for Urban Development", Eds J Teller, J Lee, C Roussey (Springer Berlin / Heidelberg) pp 85-94
- Bar-Gera H, 2007, "Evaluation of a cellular phone-based system for measurements of traffic speeds and travel times: A case study from Israel" *Transportation Research Part C: Emerging Technologies* **15** 380-391
- Barabási A-L, Albert R, 1999, "Emergence of Scaling in Random Networks" *Science* **286** 509-512
- Barros J, 2003, "Simulating urban dynamics in Latin American cities", (UK: University of Southampton)
- Barros J, 2012, "Exploring urban dynamics in Latin American cities using an agent-based simulation approach", in *Agent-Based Models of Geographical Systems* Eds A J Heppenstall, A T Crooks, L M See, M Batty (Springer Netherlands) pp 571-589
- Batty M, 1994, "A Chronicle of Scientific Planning: The Anglo-American Modeling Experience" *Journal of the American Planning Association* **60** 7 - 16
- Batty M, 2005 *Cities and complexity: Understanding cities with cellular automata, agent-based models, and fractals* (The MIT Press, Cambridge Massachusetts; London England)
- Batty M, Crooks A T, See L M, Heppenstall A J, 2012, "Perspectives on agent-based models and geographical systems", in *Agent-Based Models of Geographical Systems* Eds A J Heppenstall, A T Crooks, L M See, M Batty (Springer Netherlands) pp 1-15
- Benenson I, 1998, "Multi-agent simulations of residential dynamics in the city" *Computers, Environment and Urban Systems* **22** 25-42
- Benenson I, 1999, "Modeling population dynamics in the city: From a regional to a multi-agent approach" *Discrete Dynamics in Nature and Society* **3** 149-170
- Benenson I, Aronovich S, Noam S, 2005, "Let's talk objects: generic methodology for urban high-resolution simulation" *Computers, Environment and Urban Systems* **29** 425-453
- Benenson I, Hatna E, 2011, "Minority–Majority Relations in the Schelling Model of Residential Dynamics" *Geographical Analysis* **43** 287-305

- Benenson I, Omer I, Hatna E, 2002, "Entity-based modeling of urban residential dynamics: the case of Yaffo, Tel Aviv" *Environment and Planning B: Planning and Design* **29** 491-512
- Benenson I, Torrens P M, 2004a *Geosimulation: Automata-based modeling of urban phenomena* (John Wiley & Sons Ltd., Chichester)
- Benenson I, Torrens P M, 2004b, "Geosimulation: object-based modeling of urban phenomena" *Computers, Environment and Urban Systems* **28** 1-8
- Berling-Wolff S, Wu J, 2004, "Modeling urban landscape dynamics: A review" *Ecological Research* **19** 119-129
- Berube A, Singer A, Wilson J H, Frey W H, 2006, "Finding Exurbia: America's Fast-Growing Communities at the Metropolitan Fringe", in *Living Cities Census Series* (The Brookings Institution, Washington)
- Birkin M, Wu B, 2012, "A review of microsimulation and hybrid agent-based approaches", in *Agent-Based Models of Geographical Systems* Eds A J Heppenstall, A T Crooks, L M See, M Batty (Springer Netherlands) pp 51-68
- Blaschke T, 2010, "Object based image analysis for remote sensing" *ISPRS Journal of Photogrammetry and Remote Sensing* **65** 2-16
- Bonabeau E, 2002, "Agent-based modeling: Methods and techniques for simulating human systems" *Proceedings of the National Academy of Sciences of the United States of America* **99** 7280-7287
- Bousquet F, Le Page C, 2004, "Multi-agent simulations and ecosystem management: a review" *Ecological Modelling* **176** 313-332
- Bretagnolle A, Pumain E D e D, 2006, "From theory to modelling : urban systems as complex systems" *Cybergeo* 26
- Brown D, 2003, "Land use and forest cover on private parcels in the Upper Midwest USA, 1970 to 1990" *Landscape Ecology* **18** 777-790
- Brown D G, Johnson K M, Loveland T R, Theobald D M, 2005a, "Rural land-use trends in the conterminous United States, 1950-2000" *Ecological Applications* **15** 1851-1863
- Brown D G, Page S, Riolo R, Zellner M, Rand W, 2005b, "Path dependence and the validation of agent-based spatial models of land use" *International Journal of Geographic Information Systems* **19** 153 - 174
- Brown D G, Page S E, Riolo R, Rand W, 2004a, "Agent-based and analytical modeling to evaluate the effectiveness of greenbelts" *Environmental Modelling & Software* **19** 1097-1109
- Brown D G, Robinson D T, 2006, "Effects of heterogeneity in residential preferences on an agent-based model of urban sprawl " *Ecology and Society* **11** 46-67
- Brown D G, Robinson D T, An L, Nassauer J I, Zellner M, Rand W, Riolo R, Page S E, Low B, Wang Z, 2008, "Exurbia from the bottom-up: Confronting empirical challenges to characterizing a complex system" *Geoforum* **39** 805-818

- Brown D G, Walker R, Manson S, Seto K C, 2004b, "Modeling Land-Use and Land-Cover Change", in *Land Change Science* pp 395-409
- Bruch Elizabeth E, Mare Robert D, 2006, "Neighborhood Choice and Neighborhood Change" *American Journal of Sociology* **112** 667-709
- Bruch Elizabeth E, Mare Robert D, 2009, "Preferences and Pathways to Segregation: Reply to Van de Rijt, Siegel, and Macy" *American Journal of Sociology* **114** 1181-1198
- Brueckner J K, 2000, "Urban Sprawl: Diagnosis and Remedies" *International Regional Science Review* **23** 160-171
- Caruso G, Peeters D, Cavailhès J, Rounsevell M, 2007, "Spatial configurations in a periurban city. A cellular automata-based microeconomic model" *Regional Science and Urban Economics* **37** 542-567
- Caruso G, Peeters D, Cavailhès J, Rounsevell M, 2009, "Space - time patterns of urban sprawl, a 1D cellular automata and microeconomic approach" *Environment and Planning B: Planning and Design* **36** 968-988
- Caruso G, Rounsevell M, Cojocaru G, 2005, "Exploring a spatio-dynamic neighbourhood-based model of residential behaviour in the Brussels periurban area" *International Journal of Geographical Information Science* **19** 103 - 123
- Cavailhès J, Frankhauser P, Peeters D, Thomas I, 2004, "Where Alonso meets Sierpinski: an urban economic model of a fractal metropolitan area" *Environment and Planning A* **36** 1471-1498
- Chen Y, Irwin E G, Jayaprakash C, 2011, "An agent-based model of exurban land development", in *Agricultural and Applied Economics Association: 2011 Annual Meeting* (Pittsburgh, Pennsylvania) p 32
- Chingcuanco F, Miller E J, 2012, "A microsimulation model of urban energy use: Modelling residential space heating demand in ILUTE" *Computers, Environment and Urban Systems* **36** 186-194
- Chorley R J, Haggett P, 1967 *Models in geography* (Methuen, London)
- Clark J K, McChesney R, Munroe D K, Irwin E G, 2009, "Spatial characteristics of exurban settlement pattern in the United States" *Landscape and Urban Planning* **90** 178-188
- Clark W A V, 1986, "Residential segregation in American cities: a review and interpretation" *Population Research and Policy Review* **5** 95-127
- Clark W A V, Fossett M, 2008, "Understanding the social context of the Schelling segregation model" *Proceedings of the National Academy of Sciences* **105** 4109-4114
- Clarke M, Holm E, 1987, "Microsimulation Methods in Spatial Analysis and Planning" *Geografiska Annaler. Series B, Human Geography* **69** 145-164
- Clifford N J, 2008, "Models in geography revisited" *Geoforum* **39** 675-686
- Compas E, 2007, "Measuring exurban change in the American West: A case study in Gallatin County, Montana, 1973–2004" *Landscape and Urban Planning* **82** 56-65

- Costanza R, Ruth M, 1998, "Using Dynamic Modeling to Scope Environmental Problems and Build Consensus" *Environmental Management* **22** 183-195
- Crawford T W, Messina J P, Manson S M, O'Sullivan D, 2005, "Complexity science, complex systems, and land-use research" *Environment and Planning B: Planning and Design* **32** 792-798
- Crooks A, Castle C, Batty M, 2008, "Key challenges in agent-based modelling for geo-spatial simulation" *Computers, Environment and Urban Systems* **32** 417-430
- Crooks A T, 2006, "Exploring cities using agent-based models and GIS", in *UCL Working Paper Series, Paper 109* (University College London, London, UK)
- Crooks A T, 2008, "Constructing and implementing an agent-based model of residential segregation through vector GIS", in *UCL Working Paper Series, Paper 133* (London, UK)
- Crooks A T, 2010, "Constructing and implementing an agent-based model of residential segregation through vector GIS" *International Journal of Geographical Information Science* **24** 661-675
- Diappi L, Bolchi P, 2008, "Smith's rent gap theory and local real estate dynamics: A multi-agent model" *Computers, Environment and Urban Systems* **32** 6-18
- Dieleman F M, 2001, "Modelling residential mobility; a review of recent trends in research" *Journal of Housing and the Built Environment* **16** 249-265
- Ellis M, Holloway S R, Wright R, Fowler C S, 2011, "Agents of Change: Mixed-Race Households and the Dynamics of Neighborhood Segregation in the United States" *Annals of the Association of American Geographers* **102** 549-570
- Elvidge C D, Sutton P C, Wagner T W, Ryzner R, Vogelmann J E, Goetz S J, Smith A J, Jantz C, Seto K C, Imhoff M L, Wang Y Q, Milesi C, Nemani R, 2004, "Urbanization", in *Land Change Science* Eds G Gutman, A C Janetos, C O Justice, E F Moran, J F Mustard, R R Rindfuss, D L Skole, B L Turner, M A Cochrane (Springer Netherlands) pp 315-328
- Epple D, Platt G J, 1998, "Equilibrium and Local Redistribution in an Urban Economy when Households Differ in both Preferences and Incomes" *Journal of Urban Economics* **43** 23-51
- Epstein J M, 1999, "Agent-based computational models and generative social science" *Complexity* **4** 41-60
- Ettema D, 2011, "A multi-agent model of urban processes: Modelling relocation processes and price setting in housing markets" *Computers, Environment and Urban Systems* **35** 1-11
- Ettema D, Jong K d, Timmermans H, Bakema A, 2007, "PUMA: Multi-agent modelling of urban systems", in *Modelling Land-Use Change: Progress and applications* Eds E Koomen, J Stillwell, A Bakema, H Scholten (Springer, Dordrecht) pp 236-258
- Evans A, 2012, "Uncertainty and error", in *Agent-Based Models of Geographical Systems* Eds A J Heppenstall, A T Crooks, L M See, M Batty (Springer Netherlands) pp 309-

- Evans T P, Kelley H, 2004, "Multi-scale analysis of a household level agent-based model of landcover change" *Journal of Environmental Management* **72** 57-72
- Evans T P, Manire A, de Castro F, Brondizio E, McCracken S, 2001, "A dynamic model of household decision-making and parcel level landcover change in the eastern Amazon" *Ecological Modelling* **143** 95-113
- Ewing R H, 2008a, "Characteristics, Causes, and Effects of Sprawl: A Literature Review", in *Urban Ecology* pp 519-535
- Ewing R H, 2008b, "Characteristics, Causes, and Effects of Sprawl: A Literature Review Urban Ecology", Eds J M Marzluff, E Shulenberger, W Endlicher, M Alberti, G Bradley, C Ryan, U Simon, C ZumBrunnen (Springer US) pp 519-535
- Farmer J D, Foley D, 2009, "The economy needs agent-based modelling" *Nature* **460** 685-686
- Farooq B, Miller E J, 2012, "Towards integrated land use and transportation: A dynamic disequilibrium based microsimulation framework for built space markets" *Transportation Research Part A: Policy and Practice* **46** 1030-1053
- Feitosa F F, Le Q B, Vlek P L G, 2011, "Multi-agent simulator for urban segregation (MASUS): A tool to explore alternatives for promoting inclusive cities" *Computers, Environment and Urban Systems* **35** 104-115
- Fernandez L E, Brown D G, Marans R W, Nassauer J I, 2005, "Characterizing location preferences in an exurban population: implications for agent-based modeling" *Environment and Planning B: Planning and Design* **32** 799-820
- Filatova T, Parker D, van der Veen A, 2009a, "Agent-based urban land markets: Agent's pricing behavior, land prices and urban land use change" *Journal of Artificial Societies and Social Simulation* **12** 3
- Filatova T, Parker D C, van der Veen A, 2011a, "The Implications of Skewed Risk Perception for a Dutch Coastal Land Market: Insights from an Agent-Based Computational Economics Model" *Agricultural and Resource Economics Review* **40** 405-423
- Filatova T, van der Veen A, Parker D, 2009b, "Land market interactions between heterogeneous agents in a heterogeneous landscape -Tracing the macro-scale effects of individual trade-offs between environmental amenities and disamenities" *Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie* **57** 431-457
- Filatova T, Voinov A, van der Veen A, 2011b, "Land market mechanisms for preservation of space for coastal ecosystems: An agent-based analysis" *Environmental Modelling & Software* **26** 179-190
- Foley J A, DeFries R, Asner G P, Barford C, Bonan G, Carpenter S R, Chapin F S, Coe M T, Daily G C, Gibbs H K, Helkowski J H, Holloway T, Howard E A, Kucharik C J, Monfreda C, Patz J A, Prentice I C, Ramankutty N, Snyder P K, 2005, "Global

- consequences of land use" *Science* **309** 570-574
- Fontaine C, Rounsevell M, 2009, "An agent-based approach to model future residential pressure on a regional landscape" *Landscape Ecology* **24** 1237-1254
- Forman R T T, 2008 *Urban Region: Ecology and Planning Beyond the City* (Cambridge University Press, New York)
- Fossett M, 2006a, "Ethnic preferences, social distance dynamics, and residential segregation: Theoretical explorations using simulation analysis" *The Journal of Mathematical Sociology* **30** 185 - 273
- Fossett M, 2006b, "Including preference and social distance dynamics in multi-factor theories of segregation" *The Journal of Mathematical Sociology* **30** 289 - 298
- Fossett M, Dietrich D R, 2009, "Effects of city size, shape, and form, and neighborhood size and shape in agent-based models of residential segregation: are Schelling-style preference effects robust?" *Environment and Planning B: Planning and Design* **36** 149-169
- Fossett M, Warren W, 2005, "Overlooked Implications of Ethnic Preferences for Residential Segregation in Agent-based Models" *Urban Studies* **42** 1893-1917
- Fraser E D G, Kenney W A, 2000, "CULTURAL BACKGROUND AND LANDSCAPE HISTORY AS FACTORS AFFECTING PERCEPTIONS OF THE URBAN FOREST" *Journal of Arboriculture* **26** 106-113
- Fujita M, Ogawa H, 1982, "Multiple equilibria and structural transition of non-monocentric urban configurations" *Regional Science and Urban Economics* **12** 161-196
- Fujita M, Thisse J-F, 2002 *Economics of agglomeration: Cities, industrial location and regional growth* (Cambridge University Press)
- Galster G, 1988, "Residential segregation in American cities: A contrary review" *Population Research and Policy Review* **7** 93-112
- Geoghegan J, Wainger L A, Bockstael N E, 1997, "Spatial landscape indices in a hedonic framework: an ecological economics analysis using GIS" *Ecological Economics* **23** 251-264
- Ghoulmie F, Cont R, Nadal J-P, 2005, "Heterogeneity and feedback in an agent-based market model" *Journal of Physics: Condensed Matter* **17** S1259
- Gilbert N, Hawkesworth J C, Swinney P A, 2009, "An agent-based model of the English housing market", in *AAAI Spring Symposium: Technosocial Predictive Analytics*, AAAI, Stanford, California, USA pp 30-35
- Goodchild M F, 2004, "GIScience, Geography, Form, and Process" *Annals of the Association of American Geographers* **94** 709 - 714
- Grimm N B, Faeth S H, Golubiewski N E, Redman C L, Wu J, Bai X, Briggs J M, 2008, "Global change and the ecology of cities" *Science* **319** 756-760
- Grimm V, Railsback S F, 2005, "Chapter 1. Introduction", in *Individual-based Modeling and Ecology* Eds V Grimm, S F Railsback (Princeton University Press, Princeton,

NJ)

- Grimm V, Railsback S F, 2012, "Designing, formulating, and communicating agent-based models", in *Agent-Based Models of Geographical Systems* Eds A J Heppenstall, A T Crooks, L M See, M Batty (Springer Netherlands) pp 361-377
- Haase D, Lautenbach S, Seppelt R, 2010, "Modeling and simulating residential mobility in a shrinking city using an agent-based approach" *Environmental Modelling & Software* **25** 1225-1240
- Haase D, Schwarz N, 2009, "Simulation models on human–nature interactions in urban landscapes: A review including spatial economics, system dynamics, celular automata, and agent-based approaches" *Living Reviews in Landscape Research* **3**
- Harris B, 1985, "URBAN SIMULATION MODELS IN REGIONAL SCIENCE" *Journal of Regional Science* **25** 545-567
- Hatna E, Benenson I, 2012, "The Schelling model of ethnic residential dynamics: Beyond the integrated-segregated dichotomy of patterns" *Journal of Artificial Societies and Social Simulation* **15** 6
- Hatzopoulou M, Hao J, Miller E, 2011, "Simulating the impacts of household travel on greenhouse gas emissions, urban air quality, and population exposure" *Transportation* **38** 871-887
- Heckbert S, Smajgl A, 2005, "Analysing urban development patterns using agent based modelling: AusUrbia project report", (CSIRO Sustainable Ecosystems) p 23
- Heimlich R, Anderson W, 2001, "Development at the Urban Fringe and Beyond: Impacts on Agriculture and Rural Land", in *Agricultural Economic Report No. (AER-803)* (United States Department of Agriculture) p 88
- Herold M, Couclelis H, Clarke K C, 2005, "The role of spatial metrics in the analysis and modeling of urban land use change" *Computers, Environment and Urban Systems* **29** 369-399
- Holland J H, 1998 *Emergence: from chaos to order* (Addison-Wesley, Redwood City, California)
- Hommes C, 2005, "Heterogeneous agent models in economics and finance", in *Tinbergen Institute Discussion Paper* (CeNDEF, Department of Quantitative Economics, University of Amsterdam, and Tinbergen Institute)
- Huang Q, Parker D, Sun S, in review, "Effects of agent heterogeneity in the presence of a land-market: a systematic test in an agent-based laboratory" *Computers Environment and Urban Systems*
- International Microsimulation Association, 2012, "What is microsimulation?", <http://www.microsimulation.org/IMA/What%20is%20microsimulation.htm>
- Irwin E G, 2010, "New directions for urban economic models of land use change: Incorporating spatial dynamics and heterogeneity" *Journal of Regional Science* **50** 65-91
- Irwin E G, Bell K P, Geoghegan J, 2003, "Modeling and Managing Urban Growth at the

- Rural-Urban Fringe: A Parcel-Level Model of Residential Land Use Change" *Agricultural and Resource Economics Review* **32** 83-102
- Irwin E G, Bockstael N E, 2002, "Interacting agents, spatial externalities and the evolution of residential land use patterns" *Journal of Economic Geography* **2** 31-54
- Irwin E G, Bockstael N E, 2007, "The evolution of urban sprawl: Evidence of spatial heterogeneity and increasing land fragmentation" *Proceedings of the National Academy of Sciences* **104** 20672-20677
- Irwin E G, Geoghegan J, 2001, "Theory, data, methods: developing spatially explicit economic models of land use change" *Agriculture, Ecosystems & Environment* **85** 7-24
- Iverson L R, Cook E A, 2000, "Urban forest cover of the Chicago region and its relation to household density and income" *Urban Ecosystems* **4** 105-124
- Jackson J, Forest B, Sengupta R, 2008, "Agent-based simulation of urban residential dynamics and land rent change in a gentrifying area of Boston" *Transactions in GIS* **12** 475-491
- Jat M K, Garg P K, Khare D, 2008, "Monitoring and modelling of urban sprawl using remote sensing and GIS techniques" *International Journal of Applied Earth Observation and Geoinformation* **10** 26-43
- Jayaprakash C, Warren K, Irwin E, Chen K, 2009, "The interaction of segregation and suburbanization in an agent-based model of residential location" *Environment and Planning B: Planning and Design* **36** 989-1007
- Ji W, Ma J, Twibell R W, Underhill K, 2006, "Characterizing urban sprawl using multi-stage remote sensing images and landscape metrics" *Computers, Environment and Urban Systems* **30** 861-879
- Jjumba A, Dragičević S, 2011, "High resolution urban land-use change modeling: Agent iCity approach" *Applied Spatial Analysis and Policy* 1-25
- Johnson G W, Bagstad K J, Snapp R R, Villa F, 2012, "Service Path Attribution Networks (SPANs): A Network Flow Approach to Ecosystem Service Assessment", (IGI Global) pp 54-71
- Jordan R, Birkin M, Evans A, 2011, "Agent-Based Simulation Modelling of Housing Choice and Urban Regeneration Policy", in *Multi-Agent-Based Simulation XI* Eds T Bosse, A Geller, C Jonker (Springer Berlin Heidelberg) pp 152-166
- Jordan R, Birkin M, Evans A, 2012, "Agent-based modelling of residential mobility, housing choice and regeneration", in *Agent-Based Models of Geographical Systems* Eds A J Heppenstall, A T Crooks, L M See, M Batty (Springer Netherlands) pp 511-524
- Kalnay E, Cai M, 2003, "Impact of urbanization and land-use change on climate" *Nature* **423** 528-531
- Kennedy W G, 2012, "Modelling human behaviour in agent-based models", in *Agent-Based Models of Geographical Systems* Eds A J Heppenstall, A T Crooks, L M See,

- M Batty (Springer Netherlands) pp 167-179
- Kii M, Doi K, 2005, "Multiagent land-use and transport model for the policy evaluation of a compact city" *Environment and Planning B: Planning and Design* **32** 485-504
- Kirman A P, 1992, "Whom or what does the representative individual represent?" *The Journal of Economic Perspectives* **6** 117-136
- Kong F, Yin H, Nakagoshi N, 2007, "Using GIS and landscape metrics in the hedonic price modeling of the amenity value of urban green space: A case study in Jinan City, China" *Landscape and Urban Planning* **79** 240-252
- Lambin E F, Geist H J, Lepers E, 2003, "Dynamics of land-use and land-cover change in tropical regions" *Annual review of environment and resources* **28** 241
- Lambin E F, Turner B L, Geist H J, Agbola S B, Angelsen A, Bruce J W, Coomes O T, Dirzo R, Fischer G, Folke C, George P S, Homewood K, Imbernon J, Leemans R, Li X, Moran E F, Mortimore M, Ramakrishnan P S, Richards J F, Skånes H, Steffen W, Stone G D, Svedin U, Veldkamp T A, Vogel C, Xu J, 2001, "The causes of land-use and land-cover change: moving beyond the myths" *Global Environmental Change* **11** 261-269
- Larson K, Casagrande D, Harlan S, Yabiku S, 2009, "Residents' Yard Choices and Rationales in a Desert City: Social Priorities, Ecological Impacts, and Decision Tradeoffs" *Environmental Management* **44** 921-937
- Laurie A J, Jaggi N K, 2003, "Role of 'vision' in neighbourhood racial segregation: A variant of the Schelling segregation model" *Urban Studies* **40** 2687-2704
- Lawrence S, Giles C L, 1999, "Accessibility of information on the web" *Nature* **400** 107-107
- Li H, Wu J, 2004, "Use and misuse of landscape indices" *Landscape Ecology* **19** 389-399
- Li X, Liu X, 2007, "Defining agents' behaviors to simulate complex residential development using multicriteria evaluation" *Journal of Environmental Management* **85** 1063-1075
- Li X, Liu X, 2008, "Embedding sustainable development strategies in agent-based models for use as a planning tool" *International Journal of Geographical Information Science* **22** 21-45
- Ligmann-Zielinska A, 2009, "The impact of risk-taking attitudes on a land use pattern: an agent-based model of residential development" *Journal of Land Use Science* **4** 215 - 232
- Ligmann-Zielinska A, Jankowski P, 2007, "Agent-based models as laboratories for spatially explicit planning policies" *Environment and Planning B: Planning and Design* **34** 316-335
- Ligmann-Zielinska A, Jankowski P, 2010, "Exploring normative scenarios of land use development decisions with an agent-based simulation laboratory" *Computers, Environment and Urban Systems* **34** 409-423
- Ligmann-Zielinska A, Sun L, 2010, "Applying time dependent variance-based global

- sensitivity analysis to represent the dynamics of an agent-based model of land use change" *International Journal of Geographical Information Science* **24** 1829-1850
- Ligtenberg A, Bregt A K, van Lammeren R, 2001, "Multi-actor-based land use modelling: spatial planning using agents" *Landscape and Urban Planning* **56** 21-33
- Ligtenberg A, Wachowicz M, Bregt A K, Beulens A, Kettenis D L, 2004, "A design and application of a multi-agent system for simulation of multi-actor spatial planning" *Journal of Environmental Management* **72** 43-55
- Liu J, Dietz T, Carpenter S R, Alberti M, Folke C, Moran E, Pell A N, Deadman P, Kratz T, Lubchenco J, Ostrom E, Ouyang Z, Provencher W, Redman C L, Schneider S H, Taylor W W, 2007, "Complexity of coupled human and natural systems" *Science* **317** 1513-1516
- Liu J, Dietz T, Carpenter S R, Alberti M, Folke C, Moran E, Pell A N, Deadman P, Kratz T, Lubchenco J, Ostrom E, Ouyang Z, Provencher W, Redman C L, Schneider S H, Taylor W W, 2007, "Complexity of coupled human and natural systems" *Science* **317** 1513-1516
- Lloyd A L, May R M, 2001, "How Viruses Spread Among Computers and People" *Science* **292** 1316-1317
- Loibl W, Tötzer T, Köstl M, Steinnocher K, 2007, "Simulation of polycentric urban growth dynamics through agents: Model concept, application, results and validation", in *Modelling Land-Use Change: Progress and applications* Eds E Koomen, J Stillwell, A Bakema, H Scholten (Springer, Dordrecht) pp 219-235
- Loibl W, Toetzer T, 2003, "Modeling growth and densification processes in suburban regions - simulation of landscape transition with spatial agents" *Environmental Modelling & Software* **18** 553-563
- Lopez R, Hynes H P, 2003, "Sprawl In The 1990s: Measurement, Distribution, and Trends" *Urban Affairs Review* **38** 325-355
- Macy M W, Willer R, 2002, "From factors to actors: Computational sociology and agent-based modeling" *Annual Review of Sociology* **28** 143-166
- Magliocca N, Safirova E, McConnell V, Walls M, 2011, "An economic agent-based model of coupled housing and land markets (CHALMS)" *Computers Environment and Urban Systems* **35** 183-191
- Mahdavi B, O'Sullivan D, Davis P, 2007, "An agent-based microsimulation framework for investigating residential segregation using census data", in *MODSIM07 International Congress on Modelling and Simulation* Eds L Oxley, D Kulasiri, Modelling and Simulation Society of Australia and New Zealand, Christchurch, New Zealand pp 365-371
- Mann S, "Institutional causes of urban and rural sprawl in Switzerland" *Land Use Policy* **In Press, Corrected Proof**
- Manson S M, 2002, "Validation and verification of multi-agent systems", in *Complexity and Ecosystem Management* Ed S M Manson (Edward Elgar Publishing,

Cheltenham, UK)

- Manson S M, 2006, "Bounded rationality in agent-based models: experiments with evolutionary programs" *International Journal of Geographical Information Science* **20** 991-1012
- Manson S M, Evans T, 2007, "Agent-based modeling of deforestation in southern Yucatan, Mexico, and reforestation in the Midwest United States" *Proceedings of the National Academy of Sciences* **104** 20678-20683
- Manson S M, Sun S, Bonsal D, 2012, "Agent-based modeling and complexity", in *Agent-Based Models of Geographical Systems* Eds A J Heppenstall, A T Crooks, L M See, M Batty (Springer Netherlands) pp 125-139
- Martin C A, Peterson K A, Stabler L B, 2003, "Residential landscape in Phoenix, Arizona, U.S.: Practices and preferences relative to covenants, codes and restrictions" *Journal of Arboriculture* **29** 9-17
- Martin C A, Warren P S, Kinzig A P, 2004, "Neighborhood socioeconomic status is a useful predictor of perennial landscape vegetation in residential neighborhoods and embedded small parks of Phoenix, AZ" *Landscape and Urban Planning* **69** 355-368
- Matthews R, Gilbert N, Roach A, Polhill J, Gotts N, 2007, "Agent-based land-use models: a review of applications" *Landscape Ecology* **22** 1447-1459
- McGarigal K, Cushman S A, Neel M C, Ene E, 2002, "FRAGSTATS v3: Spatial Pattern Analysis Program for Categorical Maps", (Computer software program produced by the authors at the University of Massachusetts, Amherst. Available at the following web site: www.umass.edu/landeco/research/fragstats/fragstats.html)
- Miller E, Douglas Hunt J, Abraham J E, Salvini P A, 2008, "Microsimulating urban systems" *Computers, Environment and Urban Systems* **28** 9-44
- Miller E, Farooq B, Chingcuanco F, Wang D, 2011, "Historical validation of integrated transport-land use model system" *Transportation Research Record: Journal of the Transportation Research Board* **2255** 91-99
- Mills E S, 1972 *Studies in the Structure of the Urban Economy* (Johns Hopkins Press, Baltimore, MD)
- Monticino M, Acevedo M, Callicott B, Cogdill T, Lindquist C, 2007, "Coupled human and natural systems: A multi-agent-based approach" *Environmental Modelling & Software* **22** 656-663
- Munroe D K, 2007, "Exploring the determinants of spatial pattern in residential land markets: amenities and disamenities in Charlotte, NC, USA" *Environment and Planning B: Planning and Design* **34** 336-354
- Muth R F, 1969 *Cities and Housing: The Spatial Pattern of Urban Residential Land Use* (The University of Chicago Press, Chicago)
- Nagendra H, Munroe D K, Southworth J, 2004, "From pattern to process: landscape fragmentation and the analysis of land use/land cover change" *Agriculture, Ecosystems & Environment* **101** 111-115

- Nassauer J, 1995, "Culture and changing landscape structure" *Landscape Ecology* **10** 229-237
- Nassauer J I, 1993, "Ecological function and the perception of suburban residential landscapes", in *NC-163. General Technical Report* Ed P H Gobster (USDA Forest Service North Central Forest Experiment Station, St. Paul, MN)
- Nassauer J I, Allan J D, Johengen T, Kosek S E, Infante D, 2004, "Exurban residential subdivision development: Effects on water quality and public perception" *Urban Ecosystems* **7** 267-281
- Nassauer J I, Wang Z, Dayrell E, 2009, "What will the neighbors think? Cultural norms and ecological design" *Landscape and Urban Planning* **92** 282-292
- Nechyba T J, Walsh R P, 2004, "Urban Sprawl" *The Journal of Economic Perspectives* **18** 177-200
- Nelson A C, 1992, "Characterizing Exurbia" *Journal of Planning Literature* **6** 350-368
- Ngo T A, See L, 2012, "Calibration and validation of agent-based models of land cover change", in *Agent-Based Models of Geographical Systems* Eds A J Heppenstall, A T Crooks, L M See, M Batty (Springer Netherlands) pp 181-197
- Nolan J, Parker D, Van Kooten G C, Berger T, 2009, "An Overview of Computational Modeling in Agricultural and Resource Economics" *Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie* **57** 417-429
- O'Sullivan D, 2002, "Toward micro-scale spatial modeling of gentrification" *Journal of Geographical Systems* **4** 251-274
- O'Sullivan D, MacGill J, Yu C, 2003, "Agent-based residential segregation: A hierarchically structured spatial model", in *Proceedings of agent 2003 conference on challenges in social simulation*, The University of Chicago, Chicago, IL pp 493-507
- O'Sullivan D, Millington J, Perry G, Wainwright J, 2012, "Agent-based models - Because they're worth It?", in *Agent-Based Models of Geographical Systems* Eds A J Heppenstall, A T Crooks, L M See, M Batty (Springer Netherlands) pp 109-123
- Ogawa H, Fujita M, 1980, "Equilibrium land use patterns in a non-monocentric city" *Journal of Regional Science* **20** 455-475
- Omer I, 2005, "How ethnicity influences residential distributions: an agent-based simulation" *Environment and Planning B: Planning and Design* **32** 657-672
- Orcutt G H, 1957, "A New Type of Socio-Economic System" *The Review of Economics and Statistics* **39** 116-123
- Otter H S, Veen A v d, Vriend H J d, 2001, "ABLOoM: Location behaviour, spatial patterns, and agent-based modelling", in *Journal of Artificial Societies and Social Simulation*
- Parker D, Sun S, Filatova T, Magliocca N, Huang Q, Brown D G, Riolo R, 2012a, "The implications of alternative developer decision-making strategies on land-use and land-cover in an agent-based land market model", in *2012 International Congress on Environmental Modelling and Software, Managing Resources of a Limited Planet*,

- Sixth Biennial Meeting* Eds R Seppelt, A A Voinov, S Lange, D Bankamp, International Environmental Modelling and Software Society (iEMSs), Leipzig, Germany
- Parker D C, in review, "An economic perspective on agent-based models of land-use and land-cover change", in *The Oxford Handbook of Land Economics* Eds J M Duke, J Wu (Oxford University Press, Oxford)
- Parker D C, Berger T, Manson S M, 2002, "Agent-based models of land-use and land-cover change", in *LUCC Report Series No. 6* Eds D C Parker, T Berger, S M Manson (LUCC Focus 1 Office Anthropological Center for Training and Research on Global Environmental Change, Indiana University, Irvine, California, USA)
- Parker D C, Brown D G, Filatova T, Riolo R, Robinson D T, Sun S, 2012b, "Do land markets matter? A modeling ontology and experimental design to test the effects of land markets for an agent-based model of ex-urban residential land-use change", in *Agent-Based Models of Geographical Systems* Eds A J Heppenstall, A T Crooks, L M See, M Batty (Springer Netherlands) pp 525-542
- Parker D C, Filatova T, 2008, "A conceptual design for a bilateral agent-based land market with heterogeneous economic agents" *Computers, Environment and Urban Systems* **32** 454-463
- Parker D C, Manson S M, Janssen M A, Hoffmann M J, Deadman P, 2003, "Multi-agent systems for the simulation of land-use and land-cover change: A review" *Annals of the Association of American Geographers* **93** 314 - 337
- Parker D C, Meretsky V, 2004, "Measuring pattern outcomes in an agent-based model of edge-effect externalities using spatial metrics" *Agriculture, Ecosystems & Environment* **101** 233-250
- Polhill J G, Parker D C, Gotts N M, 2007, "Effects of Land Markets on Competition Between Innovators and Imitators in Land Use: Results from FEARLUS-ELMM", in *Social Simulation: Technologies, Advances and New Discoveries* Eds B Edmonds, K G Troitzsch, C H Iglesias (IGI Global, Hershey, Pennsylvania, USA) pp 81-97
- Pritchard D, Miller E, 2012, "Advances in population synthesis: fitting many attributes per agent and fitting to household and person margins simultaneously" *Transportation* **39** 685-704
- Rand W, M. Zellner, S. E. Page, R. Riolo, D. G., Brown a L E F, 2002, "The complex interaction of agents and environments: an example in urban sprawl.", in *Proceedings, Agent 2002: Social agents: ecology, exchange, and evolution* Eds C M a D., D Sallach, University of Chicago and Argonne National Lab, Chicago, Chicago, USA
- Ridd M K, 1995, "Exploring a V-I-S (vegetation-impervious surface-soil) model for urban ecosystem analysis through remote sensing: comparative anatomy for cities†" *International Journal of Remote Sensing* **16** 2165-2185
- Rindfuss R R, Walsh S J, Turner B L, Fox J, Mishra V, 2004, "Developing a science of

- land change: Challenges and methodological issues" *Proceedings of the National Academy of Sciences* **101** 13976-13981
- Rishbeth C, 2004, "Ethno-cultural representation in the urban landscape" *Journal of Urban Design* **9** 311-333
- Robbins P, Birkenholtz T, 2003, "Turfgrass revolution: measuring the expansion of the American lawn" *Land Use Policy* **20** 181-194
- Robinson D, 2012, "Land-cover fragmentation and configuration of ownership parcels in an exurban landscape" *Urban Ecosystems* **15** 53-69
- Robinson D T, Brown D G, 2009, "Evaluating the effects of land-use development policies on ex-urban forest cover: An integrated agent-based GIS approach" *International Journal of Geographical Information Science* **23** 1211-1232
- Robinson D T, Brown D G, Parker D C, Schreinemachers P, Janssen M A, Huigen M, Wittmer H, Gotts N, Promburom P, Irwin E, Berger T, Gatzweiler F, Barnaud C C, 2007, "Comparison of empirical methods for building agent-based models in land use science" *Journal of Land Use Science* **2** 31 - 55
- Robinson D T, Filatova T, Sun S, Riolo R L, Brown D G, Parker D C, Hutchins M, Currie W S, Nassauer J I, 2010, "Integrating land markets, land management, and ecosystem function in a model of land change", in *2010 International Congress on Environmental Modelling and Software* Eds D A Swayne, A Voinov, W Yang, T Filatova, International Environmental Modelling and Software Society (iEMSs), Ottawa, Canada p S.07.11
- Robinson D T, Murray-Rust D, Rieser V, Milicic V, Rounsevell M, 2012, "Modelling the impacts of land system dynamics on human well-being: Using an agent-based approach to cope with data limitations in Koper, Slovenia" *Computers, Environment and Urban Systems* **36** 164-176
- Robinson D T, Sun S, Hutchins M, Riolo R L, Brown D G, Parker D C, Filatova T, Currie W S, Kiger S, in press, "Effects of land markets and land management on ecosystem function: A framework for modelling exurban land-change" *Environmental Modelling & Software*
- Robinson L, Newell J P, Marzluff J M, 2005, "Twenty-five years of sprawl in the Seattle region: growth management responses and implications for conservation" *Landscape and Urban Planning* **71** 51-72
- Rosenzweig C, Solecki W, Hammer S A, Mehrotra S, 2010, "Cities lead the way in climate-change action" *Nature* **467** 909-911
- Sakoda J, 1971, "The checkerboard model of social interaction" *Journal of Mathematical Sociology* **1** 119-132
- Salvini P, Miller E J, 2005, "ILUTE: An operational prototype of a comprehensive microsimulation model of urban systems" *Networks and Spatial Economics* **5** 217-234
- Sasaki Y, Box P, 2003, "Agent-based verification of von Thünen's location theory"

- Scheffer M, Carpenter S R, Lenton T M, Bascompte J, Brock W, Dakos V, van de Koppel J, van de Leemput I A, Levin S A, van Nes E H, Pascual M, Vandermeer J, 2012, "Anticipating Critical Transitions" *Science* **338** 344-348
- Schelling T C, 1971, "Dynamic models of segregation" *Journal of Mathematical Sociology* 143-186
- Seto K C, Güneralp B, Hutyrá L R, 2012, "Global forecasts of urban expansion to 2030 and direct impacts on biodiversity and carbon pools" *Proceedings of the National Academy of Sciences*
- Skaburskis A, 2006, "New Urbanism and Sprawl: A Toronto Case Study" *Journal of Planning Education and Research* **25** 233-248
- Smajgl A, Brown D G, Valbuena D, Huigen M G A, 2011, "Empirical characterisation of agent behaviours in socio-ecological systems" *Environmental Modelling & Software* **26** 837-844
- Song Y, Knaap G-J, 2004a, "Measuring the effects of mixed land uses on housing values" *Regional Science and Urban Economics* **34** 663-680
- Song Y, Knaap G-J, 2004b, "Measuring Urban Form: Is Portland Winning the War on Sprawl?" *Journal of the American Planning Association* **70** 210 - 225
- Sun S, Parker D C, Huang Q, Filatova T, Robinson D T, Riolo R L, Hutchins M D, Brown D G, in review, "Significance and Complexity of Market Impacts on Land Use Change: An Agent-based Experiment"
- Sushinsky J R, Rhodes J R, Possingham H P, Gill T K, Fuller R A, 2012, "How should we grow cities to minimise their biodiversity impacts?" *Global Change Biology* n/a-n/a
- Talarchek G, 1990, "The urban forest of New Orleans: An exploratory analysis of relationships" *Urban Geography* **11** 65-86
- Tao H, Li X, Chen X, 2009, "Simulation for evolvement of residential spatial patterns in real scene based on multi-agent" *Acta Geographica Sinica* **64** 665-676
- Termorshuizen J, Opdam P, 2009, "Landscape services as a bridge between landscape ecology and sustainable development" *Landscape Ecology* **24** 1037-1052
- Tesfatsion L, 2006, "Agent-based computational economics: A constructive approach to economic theory", in *Handbook of Computational Economics* Eds L Tesfatsion, K L Judd (Elsevier) pp 831-880
- Theil H, 1967 *Economics and Information Theory* (North-Holland, Amsterdam)
- Theobald D M, 2001, "Land-use dynamics beyond the American urban fringe" *Geographical Review* **91** 544-564
- Theobald D M, 2004, "Placing exurban land-use change in a human modification framework" *Frontiers in Ecology and the Environment* **2** 139-144
- Theobald D M, 2005, "Landscape Patterns of Exurban Growth in the USA from 1980 to 2020" *Ecology and Society* **10** 32
- Tian G, Ouyang Y, Quan Q, Wu J, 2011, "Simulating spatiotemporal dynamics of

- urbanization with multi-agent systems - A case study of the Phoenix metropolitan region, USA" *Ecological Modelling* **222** 1129-1138
- Torrens P, 2008, "A Toolkit for Measuring Sprawl" *Applied Spatial Analysis and Policy* **1** 5-36
- Torrens P, 2012, "Urban geosimulation", in *Agent-Based Models of Geographical Systems* Eds A J Heppenstall, A T Crooks, L M See, M Batty (Springer Netherlands) pp 435-450
- Torrens P M, 2007, "A geographic automata model of residential mobility" *Environment and Planning B: Planning and Design* **34** 200-222
- Torrens P M, Nara A, 2007, "Modeling gentrification dynamics: A hybrid approach" *Computers, Environment and Urban Systems* **31** 337-361
- Turner B L, Lambin E F, Reenberg A, 2007, "The emergence of land change science for global environmental change and sustainability" *PNAS* **104** 20666-20671
- Turner M G, 1989, "Landscape Ecology: The Effect of Pattern on Process" *Annual Review of Ecology and Systematics* **20** 171-197
- Turner M G, Gardner R H, O'Neill R V, 2001 *Landscape Ecology in Theory and Practice: Pattern and Process* (Springer, New York, USA)
- Tyrväinen L, 1997, "The amenity value of the urban forest: an application of the hedonic pricing method" *Landscape and Urban Planning* **37** 211-222
- UN, 2012, "World Urbanization Prospects: The 2011 Revision", (United Nations, Department of Economic and Social Affairs/Population Division, New York)
- Valbuena D, Verburg P H, Bregt A K, 2008, "A method to define a typology for agent-based analysis in regional land-use research" *Agriculture, Ecosystems and Environment* **128** 27-36
- Verburg P H, Schot P P, Dijst M J, Veldkamp A, 2004, "Land use change modelling: current practice and research priorities" *GeoJournal* **61** 309-324
- Von Thünen J H, 1966 *Isolated state; an English edition of Der isolierte Staat* (Pergamon Press, Oxford)
- Waddell P, 2002, "UrbanSim: Modeling urban development for land use, transportation and environmental planning" *Journal of the American Planning Association* **68** 297-314
- Waddell P, Borning A, Noth M, Freier N, Becke M, Ulfarsson G, 2003, "Microsimulation of urban development and location choices: Design and implementation of UrbanSim" *Networks and Spatial Economics* **3** 43-67
- Waddell P, Wang L, Liu X, 2008, "UrbanSim: An evolving planning support system for evolving communities", in *Planning Support Systems* Ed R Brail (Lincoln Land Institute, Cambridge, MA)
- Wagner P, Wegener M, 2007, "Urban land use, transport and environment models: Experiences with an integrated microscopic approach" *disP* **170** 45-56
- Wasserman H, Yohe G, 2001, "Segregation and the provision of spatially defined local

- public goods" *American Economist* **45** 13-24
- Wu B M, Birkin M H, 2012, "Agent-based extensions to a spatial microsimulation model of demographic change", in *Agent-Based Models of Geographical Systems* Eds A J Heppenstall, A T Crooks, L M See, M Batty (Springer Netherlands) pp 347-360
- Wu B M, Birkin M H, Rees P H, 2008, "A spatial microsimulation model with student agents" *Computers, Environment and Urban Systems* **32** 440-453
- Wu J, 2008, "Landscape Ecology", in *Encyclopedia of Ecology* Eds S E Jorgensen, B Fath (Elsevier, Oxford) pp 2103-2108
- Wu J, 2010, "Landscape Ecology and Sustainability Science", in *Ecological Complexity and Ecological Vision* Eds Y Wu, J Fan (Higher Education Press, Beijing)
- Wu J, Adams R M, Plantinga A J, 2004, "Amenities in an urban equilibrium model:: Residential development in Portland, Oregon" *Land Economics* **80** 19-32
- Wu J, Jenerette G D, Buyantuyev A, Redman C L, 2011, "Quantifying spatiotemporal patterns of urbanization: The case of the two fastest growing metropolitan regions in the United States" *Ecological Complexity* **8** 1-8
- Wu J, Plantinga A J, 2003, "The influence of public open space on urban spatial structure" *Journal of Environmental Economics and Management* **46** 288-309
- Xie Y, Batty M, Zhao K, 2007, "Simulating emergent urban form using agent-based modeling: Desakota in the Suzhou-Wuxian region in China" *Annals of the Association of American Geographers* **97** 477 - 495
- Xie Y, Zhou X, 2012, "Modeling individual-level heterogeneity in racial residential segregation" *Proceedings of the National Academy of Sciences* **109** 11646-11651
- Yin L, 2009, "The dynamics of residential segregation in Buffalo: An agent-based simulation" *Urban Studies* **46** 2749-2770
- Yin L, Muller B, 2007, "Residential location and the biophysical environment: exurban development agents in a heterogeneous landscape" *Environment and Planning B: Planning and Design* **34** 279-295
- Zaidi A, Rake K, 2001, "Dynamic Microsimulation Models: A Review and Some Lessons for SAGE", in *SAGE Discussion Paper No. 2* (SAGE London) p 36
- Zellner M L, Riolo R L, Rand W, Brown D G, Page S E, Fernandez L E, 2010, "The problem with zoning: nonlinear effects of interactions between location preferences and externalities on land use and utility" *Environment and Planning B: Planning and Design* **37** 408-428